The Geography of Disadvantage: Do Cost-of-Living Adjustments Improve Poverty Measurement and Program Targeting?

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Abstract

Individuals are commonly assumed to be more disadvantaged in higher-cost areas. As a result, geographic adjustments for local prices are embedded in many federal payments and have been proposed or implemented for various poverty measures. We assess whether such adjustments achieve a central objective of a poverty measure: identifying the least advantaged population. We examine ten domains of well-being – material hardships, appliances owned, home quality, food security, public services, health, education, assets, permanent income, and mortality – drawing on 71 indicators from linked survey and administrative records. Within each domain, we contrast those classified as poor under the Supplemental Poverty Measure and the new Comprehensive Income Poverty Measure, with and without a geographic adjustment. In nine of ten domains, we find that incorporating a geographic adjustment instead identifies a less deprived poor population. This result reflects local prices being sufficiently correlated with public goods and locational amenities that those with low incomes appear less disadvantaged in higher-cost areas. Because poverty thresholds underpin eligibility for many transfer programs and the geographic allocation of federal funding, geographic adjustments may direct resources away from the most disadvantaged.

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1. Introduction

Where in the United States are individuals the most disadvantaged? Answers to this question can determine how billions of dollars in federal funding are allocated, not least because government programs frequently target certain geographic areas. Title I and Opportunity Zones allocate funds based on local poverty rates, while Empowerment Zones and Community Development Block Grants target areas along additional dimensions like unemployment rates and housing supply. Federal policy also differentiates across geographic areas in benefit levels for individuals. Eligibility and benefits for federal housing assistance depend on incomes and fair market rents that vary across metropolitan and non-metropolitan areas, and maximum benefit amounts for the Supplemental Nutrition Assistance Program (SNAP) and school meal reimbursement rates are higher in Alaska and Hawaii than in the 48 continental states.

A common answer points to places where conventionally-measured prices, particularly housing costs, are highest. In FY 2025, the median rent paid for a 2-bedroom apartment in New York City was $2,845, nearly three times the corresponding figure in Monroe County, Mississippi ($958).[1] Given these differences, should someone living in New York City be considered poorer than someone with the same nominal income in rural Mississippi? In other words, should poverty thresholds be adjusted to reflect geographic differences in the cost of living? Geographic adjustments, particularly for housing costs, are widely favored in the recent policy literature.[2] The Official Poverty Measure (OPM) does not incorporate a geographic adjustment, but the Census Bureau's Supplemental Poverty Measure (SPM) adjusts its thresholds for geographic differences in housing prices (U.S. Census Bureau 2025), and Canada's low-income cutoffs vary by community size and urban or rural residence (Statistics Canada 2016). By classifying fewer people as poor in lower-cost areas and more people as poor in higher-cost areas, such adjustments sharply change how researchers characterize poverty and how policymakers allocate anti-poverty efforts.

[1] These amounts are derived from the Department of Housing and Urban Development (HUD) estimates of the 50th percentile of rent by geographic location.

[2] In its *Measuring Poverty* report, the National Research Council (1995) recommended that "poverty thresholds should be adjusted for differences in the cost of housing across geographic areas of the country" (p. 183). More recently, the National Academies of Sciences, Engineering, and Medicine (2023) recommended that the proposed Principal Poverty Measure "continue to reflect geographic differences in housing costs," using HUD Fair Market Rents (Recommendation 5-5).

Yet researchers remain divided as to whether geographic adjustments are conceptually justified.[3] A long literature holds that consumers are willing to pay more in certain areas to consume higher-quality amenities (Rosen 1974, Haurin 1980, Roback 1982). As a result, spatial variation in housing prices may simply reflect variation in public goods and amenities like school quality, health care, and employment opportunities (Oates 1969, Epple 2008, Brueckner 2011). Existing price indices fail to capture a number of characteristics that affect locational desirability to low-income families. These include not only housing amenities, but also the range of available goods and services, the time costs of obtaining them, and public goods such as the generosity and accessibility of safety net programs (Glaeser, Kolko, and Saiz 2001, Murphy 2016, Couture and Handbury 2020). However, the difficulties of estimating hedonic models make it difficult to fully account for these characteristics. Omitted variable bias already complicates identifying the marginal values of amenities (Greenstone 2017), and constructing an appropriate price index requires identifying their average values – which demands even more information. Given these limitations, the practical case for geographic adjustments remains unresolved.

In this paper, we assess whether geographic adjustments – those currently in use and others that have been proposed – help identify the most disadvantaged population. Several key studies have considered this to be the central goal of a poverty measure (see, e.g., Ruggles 1990, National Research Council 1995), and it is consistent with how researchers and the broader public use poverty measures as indicators of disadvantage and predictors of negative outcomes. Even if one conceives of poverty as income below a minimum standard, income can be difficult to measure accurately, so other indicators of material well-being correlated with true income can aid in measuring the truth. Importantly, a poverty measure that identifies the most disadvantaged also helps target government transfers to the most needy. A wide variety of programs determine benefit eligibility using a poverty cutoff or some multiple of a poverty line, constructed from a resource measure conceptually similar to that of the OPM.[4]

We use two Census surveys for our analyses: the Current Population Survey's Annual Social and Economic Supplement (CPS), the source of official poverty estimates, and the Survey

[3] For example, an earlier set of government reports highlighted conceptual and data limitations of geographic adjustments and noted that such adjustments may not reflect other regional differences such as the level of assistance to low-income families (U.S. Department of Health, Education, and Welfare 1976, General Accounting Office 1995).
[4] These programs include SNAP, free and reduced-price school meals, Head Start, and the Low Income Home Energy Assistance Program (LIHEAP) (see here for a list of programs that use poverty guidelines in determining eligibility).

of Income and Program Participation (SIPP), thought to have the most accurate U.S. income information. In each, we compute the SPM and the new Comprehensive Income Poverty Measure (CIPM) – which measures incomes more accurately using linked survey and administrative data – with and without a geographic adjustment. To compare poverty measures on an equal footing, we hold the share of individuals in poverty constant across alternative measures, proportionately adjusting cutoffs as needed. This amounts to comparing well-being levels between high- and low-cost areas, holding nominal income constant. Specifically, we compare those classified as poor only under the unadjusted measure (i.e., the "non-geographic-only poor," who tend to live in lower-cost areas) to those classified as poor only under the adjusted measure (i.e., the "geographic-only poor," who tend to live in higher-cost areas). This strategy builds on previous work showing that one can evaluate a proposed change to a poverty measure by examining deprivation among those classified as poor with and without the change (e.g., Meyer and Sullivan 2003, 2011, 2012, Renwick 2018, Fox and Warren 2018, Renwick 2019, Meyer et al. 2021). We examine ten domains of well-being spanning 71 individual indicators: material hardships, appliances owned, home quality issues, food security, public services, health, education, and assets from survey reports, along with permanent income and mortality from administrative records.

Applying a geographic adjustment replaces one in ten of those counted as poor with individuals in higher-cost areas. In rural areas, for example, the poverty rate falls by up to 28%. For nine of the ten domains of well-being, our summary indicator shows that the geographic-only poor are less deprived than the non-geographic-only poor, under either the SPM or CIPM. The differences are often substantial, with the geographic-only poor having roughly twice the permanent income of the non-geographic-only poor in the CPS. These general patterns hold across a range of extensions and robustness checks, including partial adjustments that scale the geographic factor, Regional Price Parities (which cover a broader bundle of goods) as the adjustment index, deep and near poverty thresholds, and the OPM as the poverty measure. Low-income individuals in lower-cost areas thus appear more disadvantaged than their counterparts in higher-cost areas, implying that geographic adjustments would target transfers and place-based funding toward a less deprived population.

Our results can be explained by the empirical fact that local prices are strongly associated with many characteristics that matter to those with low incomes. Wages have been found to rise almost one for one with prices (DuMond, Hirsch, and Macpherson 1999, Hirsch 2011), a result we

confirm in the CPS. Public goods capitalized into home prices and rents – such as schools (Tiebout 1956, Oates 1969, Black 1999, Epple 2008), pollution (Davis 2004, Chay and Greenstone 2005), and cash welfare (Glaeser 1998) – likewise vary across areas, and we find that the elasticity of state and local spending with respect to prices exceeds one for welfare, elementary and secondary education, environment and housing, and police. Such advantages can offset the additional resources needed to maintain a given standard of living where prices are higher. Consistent with this, we find that measures of intergenerational mobility – using data from the Opportunity Atlas (Chetty et al. 2018) – are positively correlated with local prices.

Our paper relates to a growing literature that analyzes the geography of deprivation. Chetty et al. (2014) investigate the spatial distribution of intergenerational mobility across commuting zones. Shaefer, Edin, and Nelson (2020) examine the variation across communities in an index of deep disadvantage spanning income, health, and social mobility. Diamond and Moretti (2021) estimate the standard of living by commuting zone, proxied by consumption, and relate it to local cost of living. Larrimore (2025) evaluates how geographic adjustments to poverty thresholds affect the identification of financial hardship. We depart from the existing literature in at least two crucial ways. First, rather than analyzing only one or two dimensions of well-being, we assemble evidence across ten domains, allowing us to characterize deprivation broadly rather than through any single lens. Second, rather than studying the entire population, we focus on the poor and use linked survey and administrative data to measure the bottom of the income distribution as accurately as possible.

The remainder of the paper proceeds as follows. Section 2 presents a simple model of how local poverty thresholds should vary with local prices and other characteristics, and reviews the theoretical and empirical literature on geographic adjustments. Section 3 describes our data and explains how we calculate poverty measures with and without a geographic adjustment. Section 4 presents descriptive statistics on how poverty rates change under a geographic adjustment. Section 5 discusses our well-being measures and analytical methods. Section 6 presents the main results, Section 7 shows extensions and robustness checks, and Section 8 provides empirical explanations for our findings. Section 9 concludes.

2. Theory and Previous Literature

2.1. A Simple Model of Local Poverty Thresholds

We begin with a simple model, based on Glaeser (2011), of how local poverty thresholds should change as local prices change. We assume that the goal of poverty assessment is to identify those suffering the greatest deprivation, though other goals are possible.[5] Suppose households have a well-defined indirect utility function $V(Y, P, \mathbf{A})$, where Y is income, P is prices, and $\mathbf{A}$ is a vector of amenities. Assume that income and amenities enter positively ($V_Y \geq 0$, $V_{A_j} \geq 0 \; \forall A_j \in \mathbf{A}$) and prices enter negatively ($V_P \leq 0$). For simplicity, we treat P as a scalar (e.g., P may be the price for a single good like housing or a composite price index for a basket of goods). Following Glaeser, we classify a household as poor if its value of $V(Y, P, \mathbf{A})$ falls below a minimum deprivation level $\underline{V}$. Let Y_0^* designate the income level in location 0 such that $V(Y_0^*, P_0, \mathbf{A}_0) = \underline{V}$. In other words, Y_0^* can be thought of as the "poverty threshold" in location 0 – i.e., for a given set of prices P_0 and amenities $\mathbf{A}_0$ in location 0, incomes below Y_0^* will lead to deprivation levels below $\underline{V}$.

Using this setup, we analyze how the appropriate poverty threshold changes as other determinants of utility change. We make an additional modification to the framework in Glaeser (2011) by including hourly wages w and unmeasured income N as additional inputs into indirect utility. Both enter positively into indirect utility ($V_w \geq 0$, $V_N \geq 0$) and are key determinants of utility that vary geographically. N can include income that is under-reported or omitted from standard income measures, ranging from housing assistance and child support to Medicaid to uncompensated hospital care. We can then totally differentiate $V(Y^*, P, \mathbf{A}, w, N) = \underline{V}$ to obtain:

$$V_Y dY^* + V_P dP + \sum_j V_{A_j} dA_j + V_w dw + V_N dN = 0.$$

Rearranging terms and dividing by dP yields:

$$\frac{dY^*}{dP} = -\frac{V_P}{V_Y} - \sum_j \frac{V_{A_j}}{V_Y}\frac{dA_j}{dP} - \frac{V_w}{V_Y}\frac{dw}{dP} - \frac{V_N}{V_Y}\frac{dN}{dP},$$

which gives an expression for how the appropriate poverty threshold changes with prices. Applying Roy's Identity gives:

[5] For example, the goal could be to determine the number of people who cannot purchase a certain set of goods in each geographic area, or to determine where the marginal utility of transfers is the highest.

$$\frac{dY^*}{dP} = \underbrace{X}_{\geq 0} - \underbrace{\sum_j \frac{V_{A_j}}{V_Y}\frac{dA_j}{dP}}_{\geq 0} - h\underbrace{\frac{dw}{dP}}_{\geq 0} - \underbrace{\frac{V_N}{V_Y}\frac{dN}{dP}}_{\geq 0}, \quad (1)$$

where X is some base consumption level and h is some base level of hours worked.

Consider first the (unrealistic) case in which amenities, hourly wages, and non-labor income are uncorrelated with prices. The right side of equation (1) then reduces to X. In other words, in the absence of all other terms, higher prices require a higher poverty threshold to maintain the same level of consumption. However, the presence of the amenity, wage, and unmeasured income terms counteract and can even reverse this naïve price correction. Amenities such as school quality and clean air are well established to be positively correlated with prices, and we empirically find that higher-price areas have higher hourly wages and higher levels of non-labor income sources. If dA_j/dP (for a given amenity indexed by j), dw/dP, and dN/dP are sufficiently positive, then the appropriate threshold Y^* could potentially be decreasing in prices. Importantly, this does not require spatial equilibrium to hold for those near the poverty line, which would imply that amenities and wages exactly offset higher nominal prices. It requires only that local amenities and incomes be strongly correlated with local prices for those in poverty.

2.2. Prices, Amenities, and the Desirability of Adjustments

The canonical spatial equilibrium framework of Rosen (1974), Haurin (1980), and Roback (1982) holds that wages and rents in equilibrium must adjust so that workers – who value amenities alongside wages and cost-of-living – are indifferent between locations with differing amenity levels. Specifically, in a location with higher amenities, Roback shows that willingness to pay for those amenities can be recovered as the sum of higher housing costs and lower wages there. More recent work relaxes the model's assumptions, allowing heterogeneous labor and non-tradable consumption goods (Roback 1988, Gyourko and Tracy 1991, Moretti 2011), but the central implication remains intact: nominal wages and prices adjust to differences in amenities across localities. The sorting mechanism behind this result was established earlier by Tiebout (1956) and Oates (1969), with households selecting communities on the basis of public goods provision and bidding up housing prices where provision is greatest.

In applying this approach to the poor, one should recognize that price adjustments to local amenities may be largely determined by the amenities valued by the non-poor population. Prices may then fail to reflect wages in the low-wage labor market or the availability of support through

welfare programs for the least well off. In that case, price adjustments cannot make all geographic areas equally desirable to the poor. Migration costs and restrictions on wage adjustments, such as minimum wage laws, could have a similar effect. Even so, the framework clarifies what an optimal adjustment would require – i.e., all characteristics of geographic areas affecting their desirability, as valued by low-resource families. That requirement is demanding, if not unattainable. Constructing such an index means estimating the value of all relevant amenities (Blomquist, Berger, and Hoehn 1988, Gyourko and Tracy 1991), and empirical work finds overwhelming evidence that amenities matter but great difficulty in pinning down their values.[6] Greenstone (2017) argues that the omitted variable problem is so overwhelming that reliable estimates of the marginal value of amenities can only be obtained under special circumstances –- and a price adjustment requires average rather than marginal valuations, which is harder still (Kaplow 1995, Greenstone 2017).

Closely related to the geographic adjustment of poverty thresholds, two papers examine the circumstances under which equity and efficiency are improved by tax and transfer payments that differ across geography. Kaplow (1995) finds that adjusting transfers for cost-of-living differences would be efficient and equitable in a benchmark case of equal utility across regions, while adjustments using standard price indices may be counterproductive when nominal cost-of-living differences are systematically correlated with amenity differences. Glaeser (1998) reaches a similar conclusion by calibration, finding that a one percent increase in prices should optimally raise transfers by 0.33 percent relative to total income, and that this elasticity never exceeds one under any parameter combination he considers. In contrast, actual programs index far more aggressively. Using data on AFDC (Aid to Families with Dependent Children, the precursor to Temporary Assistance for Needy Families or TANF), Glaeser estimates an elasticity of transfer payments with respect to local prices exceeding 1.5, and concludes that the observed level of indexing by geography appears too strong to be optimal. Taken together, these considerations point away from a full price adjustment, even if it does not fully settle its consequences for the poor.

2.3. Existing Evidence on Geographic Adjustment and Deprivation

Several papers assess geographic adjustments by comparing the material deprivation of those classified as poor with and without an adjustment, although the evidence to date is limited

[6] As Glaeser (2011) succinctly summarizes, "unobserved amenity differences bedevil local price measurement."

in scope. In a supplementary analysis to their main results, Meyer and Sullivan (2012) find that geographically adjusting SPM thresholds yields a poor population more likely to be covered by private health insurance and with higher levels of education, although they do not test significance. Renwick (2018, 2019) correlates state poverty rates under four geographically adjusted price indices with a state-level multi-dimensional deprivation index, finding that three of the four are less correlated with deprivation than the unadjusted measure. Baker, Currie, and Schwandt (2019) find that higher-poverty areas in Canada have higher mortality when poverty is measured without a geographic adjustment. Under the official low income cut-offs (LICO), which vary geographically with city size, the relationship reverses among some age groups. Larrimore (2025), which cites an earlier version of this paper, provides perhaps the closest parallel to our approach. He finds that unadjusted state poverty rates are positively correlated with financial distress (using the Consumer Financial Protection Bureau's Financial Well-Being Scale), while the SPM's geographic adjustment shifts poverty toward areas reporting less hardship.

Diamond and Moretti (2021) reach a different conclusion, finding higher consumption among low-income residents of more affordable commuting zones. However, several features of their design may account for this. They measure standard of living across commuting zones, which are predominantly metropolitan. This means that residents of non-metropolitan (rural) areas are largely omitted, and their consumption patterns may differ substantially. The sample is further limited to households with a bank account and annual income above $10,000, excluding many of the lowest-income households who may be unbanked. Finally, the authors' main outcome of interest – consumption expenditures tied to bank transactions – may be a better proxy of well-being for those higher in the income distribution than at the bottom, where measures of material hardships and mortality risk may be more revealing.

The existing body of work is suggestive but limited in ways our analysis addresses. Meyer and Sullivan (2012) do not test significance, and Renwick (2018, 2019) tests only some comparisons. Renwick's analysis also uses state averages rather than individual data, making it informative about differences across states but less so about differences by family type, race, age, or finer geography. It also does not hold the poverty rate constant across measures, nor does it control for demographic differences across states that might confound the comparisons. In addition, most prior studies examine only one or two dimensions of well-being. Our analysis

instead assembles evidence across ten domains using individual-level data, leveraging both survey and administrative data to measure poverty status and selected well-being outcomes.

3. Data and Poverty Measures

This section describes our survey and administrative data and the methods used to link them, followed by the two core poverty measures we analyze – the Supplemental Poverty Measure (SPM) and the Comprehensive Income Poverty Measure (CIPM). For each poverty measure, we focus on four ingredients: the resource measure, the resource-sharing unit, the poverty threshold, and the equivalence scale used to set thresholds for families differing in size or composition. We then describe the price indices used to adjust thresholds geographically and our procedure for anchoring poverty rates across measures. We focus on reference year 2010, since this is a year for which we have a relatively complete set of administrative records covering all income sources.

3.1. Data Sources

Survey Data

Our survey data come from the 2011 Current Population Survey Annual Social and Economic Supplement (CPS) and the 2008 Panel of the Survey of Income and Program Participation (SIPP). Both are designed to be representative of the civilian non-institutional population of the United States, collecting detailed income and demographic information for all individuals residing in sampled households. The SIPP additionally fields topical modules on material well-being. The 2011 CPS interviewed 75,000 households between February and April of 2011 about their incomes in calendar year 2010. The 2008 SIPP followed 42,000 households for up to 16 four-month waves, with attrition reducing the number observed in later waves.

The reference period in the CPS is a calendar year, while the reference period in the SIPP is four consecutive months. We therefore combine information across SIPP interview waves to calculate annual incomes. Specifically, we take as our analysis sample all individuals appearing in reference month 4 of Wave 6 (April-July 2010), incorporate survey incomes from other months of 2010 in which they appear, and proportionately scale up survey incomes for the 21% of individuals interviewed for only a portion of the year. This makes the CPS and SIPP income measures more comparable and aligns the SIPP reference period with that of the linked calendar year tax data.

Administrative Data

We also draw on a number of administrative data sources. Earnings come from multiple tax sources (including Internal Revenue Service (IRS) Form W-2, the Detailed Earnings Record database of the Social Security Administration (SSA), and IRS Form 1040), asset income (interest and dividends) from IRS Form 1040, and retirement distributions from IRS Form 1099-R. We simulate tax liabilities and credits from line items on 1040s. Program participation records from government agencies include those for Social Security, Supplemental Security Income (SSI), Service-Connected Disability payments to veterans, and HUD housing assistance. We do not use administrative data on SNAP or TANF, since these are available only for a subset of states and we want our analysis sample to cover every state in the nation. We also use administrative records to construct measures of well-being, drawing on IRS records from tax years 2008, 2009, 2011, and 2012 to construct permanent income and the SSA Numident file to calculate mortality. Appendix Section A.1 provides additional details about the survey and administrative data sources.

Linking Data Sources

We link survey and administrative data sources using individual identifiers called Protected Identification Keys (PIKs). PIKs are created by the Census Bureau's Person Identification Validation System from a reference file of Social Security Numbers linked to names, addresses, and dates of birth (Wagner and Layne 2014). Our survey analyses use the full CPS or SIPP sample and original survey weights. For most analyses using linked administrative data, we restrict the sample to individuals whose sharing units have at least one member with a PIK and, in the CPS, no whole-imputed member.[7] To account for the bias arising from non-randomly missing PIKs (and whole imputations in the CPS), we divide survey weights by the predicted probability that a sharing unit is included in this sample, conditional on observable characteristics in the survey.

3.2. Poverty Measures

Supplemental Poverty Measure (SPM)

Because the SPM is well-documented in the existing literature, we describe it briefly here and provide fuller detail in Appendix Section A.2. Its resource measure is pre-tax money income

[7] In the specific case of analyzing individual-level mortality (from the SSA Numident) while relying on survey income, we restrict our sample to individuals who link to a PIK and adjust for non-PIKing at the individual level.

plus non-cash transfers, net of taxes and certain expenses. This covers a fuller set of resources available for consumption than the pre-tax money income used by the Official Poverty Measure (OPM). We calculate the SPM resource measure using survey information only, following Fox (2019) for the CPS and Short (2014) for the SIPP. The SPM resource unit consists of an OPM family – defined as all people living together related by birth, marriage, or adoption – plus cohabiting partners, unrelated children under 15, and foster children aged 15 to 22.

The SPM threshold for a unit can be written as:

$$SPM\ Threshold_{ten,ac,sm} = (Base\ Threshold)_{ten} \times \frac{(Equivalence\ Scale\ Factor)_{ac}}{E} \times [(Housing\ Share_{ten} \times MRI_{sm}) + (1 - Housing\ Share_{ten})], \quad (2)$$

where *ten* is the unit's housing tenure, *a* and *c* index the number of adults and children in the unit, and *s* and *m* denote the unit's state and metropolitan statistical area (MSA). The first term in equation (2) is the base threshold, which is 1.2 times the average spending on food, shelter, clothing, and utilities among those in the 30th-36th percentiles of such spending, calculated separately for three housing tenure groups. The second term is a three-parameter equivalence scale, divided by the scale for a two-adult, two-child unit (denoted by the constant *E*). The final term is the geographic adjustment factor, which scales the threshold by the Median Rent Index (MRI) weighted by the share of expenditures taken up by housing costs.

Comprehensive Income Poverty Measure (CIPM)

For the second poverty measure that we analyze (the CIPM), we bring in administrative data to measure incomes more accurately while making several conceptual changes to the resource measure. First, we replace survey reports or imputations of asset income (interest and dividends), retirement income, Social Security, SSI, veterans' benefits, and tax liabilities and credits with their administrative counterparts, and we combine survey and administrative sources to construct improved measures of earnings and housing assistance. Second, in line with the OPM and in contrast with the SPM, the CIPM does not subtract expenses for work, childcare, child support, and health care. While subtracting these expenses may theoretically yield a resource measure that better approximates the resources available for consumption, prior research finds that subtracting

certain expenses (such as medical costs) identifies a poor population that appears less materially deprived (Meyer and Sullivan 2012). Third, the CIPM estimates a flow value of services from home and car ownership as well as an annuity value of other net assets. Because the CPS does not ask about assets in detail, we estimate these asset flows only in the SIPP.

The CIPM uses the same resource unit as the SPM and nearly the same poverty thresholds. The key difference is that the base threshold and the housing share in the geographic adjustment factor no longer vary by housing tenure. Because the CIPM resource measure explicitly accounts for the flow value of home ownership, there is no longer a reason to set distinct thresholds for distinct housing status groups, which implicitly accounts for differences in available resources.

3.3. Geographic Adjustments

Our geographically adjusted versions of both the SPM and CIPM use the Median Rent Index (MRI), which is calculated from 5-year American Community Survey (ACS) files as the ratio of an area's median gross rent for a two-bedroom unit with a complete kitchen and bathroom to the median gross rent for the same unit type in the U.S. The MRI is calculated separately for 358 geographic areas, comprising 264 publicly identified MSAs, non-metropolitan areas in 48 states, and "other" metropolitan areas in 46 states. As an alternative, we consider Regional Price Parities (RPPs), which cover a broader set of goods (Aten 2005, Aten and D'Souza 2008). Calculated by the Bureau of Economic Analysis (BEA), RPPs measure price differences across two hundred individual items comprising eight categories: housing, transportation, food, education, recreation, medical, apparel, and other. Appendix Section A.3 contains additional detail on these and other price indices.[8]

To construct the SPM and CIPM without a geographic adjustment, we remove the geographic adjustment factor from the poverty threshold, leaving just the product of the base threshold and equivalence scale. For both the SPM and CIPM, with and without a geographic adjustment, we proportionately scale thresholds so that the poverty rate is always fixed at 15.1%, which was the official poverty rate for 2010. Switching between poverty measures therefore

[8] Two related indices have been proposed that we do not incorporate. Renwick (2018, 2019) proposes a rescaled MRI, which cuts the variation in the MRI in half on the grounds that the MRI over-adjusts thresholds if places with higher median rents also have greater amenities; Renwick notes this adjustment is admittedly "arbitrary" because the literature has established no clear methodology for incorporating amenities (p. 5). Food, apparel, and rent regional price parities (FAR RPPs) cover only the subset of goods in RPPs that also enter the SPM threshold (Renwick et al. 2014, Renwick et al. 2017).

changes only the ranking of individuals, not the absolute number counted as poor. Anchoring the rates precludes us from concluding that one measure yields a more deprived population simply because it selects a smaller and more targeted segment of the poor. Figure 1 shows the fixed proportions by which we scale the SPM and CIPM to anchor poverty at 15.1% in both the CPS and SIPP. The proportions applied to the SPM thresholds range from 0.97 to 1.04, while those for the CIPM are approximately 1.46 in the CPS and 1.68-1.69 in the SIPP. These differences reflect the CIPM using administrative data to correct for underreported survey incomes, adding asset flows in the SIPP, and not subtracting expenses from the resource measure.

4. Descriptive Evidence

This section provides descriptive evidence of how a geographic adjustment changes measured poverty rates by geography, race/ethnicity, and family type.

4.1. Changes in Poverty Rates by Geography

Figure 2 shows how poverty rates change with a geographic adjustment at two levels of geography, with the national rate anchored to 15.1%. We focus on the SPM in the public-use CPS, as many of these estimates are based on small sample sizes that create disclosure concerns in restricted-use data. Panel (a) shows changes by state, while Panel (b) shows changes at the core-based statistical area (CBSA) level. A CBSA is the finest geography identifiable in the public-use CPS and consists of one or more counties anchored by an urban center of at least 10,000 people plus adjacent counties with high commuting ties to that center. Counties outside a publicly identified CBSA are classified within a state as either "other metropolitan" or "non-metropolitan."

The states in Panel (a) whose poverty rates increase most with a geographic adjustment are concentrated in coastal areas with typically high rents – namely New England, the mid-Atlantic, and the West Coast. Connecticut, California, Hawaii, Maryland, Massachusetts, and New Jersey each see increases of 25% or more. In contrast, poverty rates fall in the Deep South, Appalachia, and the Midwest – where housing rents are typically low – with declines of at least 25% in Arkansas, Iowa, Kentucky, Mississippi, North Dakota, South Dakota, and West Virginia. One might thus conclude that state-level differences in rental costs drive most of this variation. Yet Panel (b) shows substantial variation within states as well, specifically between urban and rural areas. For example, California's poverty rate rises by 37% at the state level (driven by increases

in the urban areas of Los Angeles, San Diego, and San Francisco), while rural areas in the San Joaquin Valley actually see decreases in poverty. Conversely, while Mississippi's poverty rate falls by 26% at the state level (driven by declines in its more rural areas), the urban areas of Jackson and Hattiesburg see declines of less than 12.5%. More generally, a geographic adjustment raises poverty rates in urban clusters and lowers them in rural areas.

Table 1 sheds further light by reporting poverty rates without a geographic adjustment alongside the change from applying one, conditional on a set of characteristics. Columns 1-4 use the SPM and Columns 5-8 use the CIPM, with each set reporting estimates in the CPS followed by the SIPP. Using the SPM in the CPS, the rural poverty rate falls by 2.6 percentage points (from 14.0% to 11.4%) after a geographic adjustment. This large and statistically significant decline corroborates the core pattern in Figure 2b, that a geographic adjustment indicates less poverty in rural areas. The decline is larger in the SIPP, and similar patterns hold using the CIPM. Across the nine Census divisions, poverty rates increase following a geographic adjustment in New England (2.1 percentage points), the Mid-Atlantic (1.3 points), and the Pacific (4.3 points), and fall in the remaining six. The largest declines are in East South Central (4.5 points), West North Central (2.3 points), and West South Central (2.0 points). Each difference is statistically significant at the 1% level except for South Atlantic, which is significant at the 5% level. These patterns are again consistent with Figure 2 and largely hold using the CIPM and in the SIPP.

4.2. Changes in Poverty Rates for Other Groups

Table 1 also reports poverty rates by the race/ethnicity of the sharing unit head and by family type. Using the SPM in the CPS, a geographic adjustment classifies significantly more Asian- and Hispanic-headed units in poverty (by 2.4 percentage points each), while the differences for white-, black-, or other race-headed units are not statistically significant. The increases for Asian and Hispanic units may be driven by the substantial increases in the Pacific region, which has large Asian and Hispanic populations. A geographic adjustment also classifies fewer elderly and single parent families and more multiple parent families as poor, while the differences for single childless and multiple childless units are statistically insignificant. Many of these patterns persist in the SIPP and using the CIPM. Using the SPM in the SIPP, black- and other race-headed units now see slight decreases. Using the CIPM in the CPS, poverty rates decrease significantly

for white and elderly units and increase for Asian, Hispanic, and multiple parent units. In the SIPP, they decrease for elderly and single childless units and increase for Asian and Hispanic units.

5. Methods

This section describes the measures of well-being we analyze and the empirical methods used to compare well-being across poverty measures.

5.1. Measures of Material Well-Being

We analyze ten domains of well-being indicators spanning 71 individual indicators. Four domains – permanent income, mortality, education, and health – are available in both the CPS and SIPP, either because they derive from administrative data or because they are asked about in both surveys. Six domains are specific to the SIPP: material hardships, home quality problems, appliances owned, assets owned, food security, and public services and safety. We chose these indicators *ex ante*, and they constitute a broader set than those used in Meyer et al. (2021). These indicators also overlap with those in Fox and Warren (2018) and Iceland, Kovach, and Creamer (2021).[9] Appendix Section A.4 lists every indicator and its source.

Permanent income comes from tax records and is defined as the sum of income for 2008, 2009, 2011, and 2012, converted to 2010 dollars using the PCE deflator. For filers, we use Adjusted Gross Income (AGI) reported on Form 1040; for non-filers, we use the sum of incomes reported on Forms W-2 and 1099-R.[10] We analyze permanent income at the SPM unit level, adjusted according to the equivalence scale recommended in National Research Council (1995).[11] Next, we construct two measures of mortality from the SSA Numident file: having died by December 31, 2015 and having died by March 1, 2019, each assessed at the level of both the individual and SPM unit head. Years of education for the unit head is computed from the survey

[9] While our well-being indicators provide a useful framework for understanding the circumstances of those in poverty, they may be less suitable for understanding the circumstances of those in the middle class or with higher incomes more broadly. This is because many of these indicators reflect "tail events" that may not be particularly relevant for those outside of poverty. Other authors have examined similar indicators as proxies for disadvantage. For example, Fusaro, Shaefer, and Simington (2021) analyze the geographic distribution of an index of "deep disadvantage," with components ranging from low birthweight and life expectancy to education status and unemployment rate.

[10] We use AGI for filers because it is the broadest line item for which we have complete information (i.e., we do not have complete information on total money income). We also use Forms W-2 and 1099-R for non-filers because these are the only two information returns for which we have monetary amounts.

[11] The equivalence scale is of the form $(A + PK)^F$, where A and K respectively designate the number of adults and children in the SPM unit. Following Meyer and Sullivan (2012), we set $P = F = 0.7$.

report of the highest grade completed. We also examine self-reported health in both the CPS and the SIPP, using an indicator for fair or poor health quality at both the head and individual levels. In the SIPP, we additionally examine indicators for having a condition that limits the kind or amount of work you can do and for having a condition that prevents work.

The six SIPP-only domains come from topical modules that are linked to the core survey files. Material hardships (eight indicators), home quality problems (seven), appliances owned (eight), food security (eight), and public services and safety (twelve) come from the Wave 6 module, with the individual indicators in each listed in Appendix Section A.4. For material hardships, home quality problems, and appliances owned, we use the same variables as Meyer et al. (2021). Assets come from the Wave 4 and 7 modules and comprise six measures: total wealth, total debt, net worth, home equity, vehicle equity, and other assets.

For each domain we designate a single summary measure. Because four domains are available in both surveys and six domains are available only in the SIPP, this gives fourteen summary measures in total. For the five domains consisting of binary items – material hardships, home quality problems, appliances owned, food security, and public services and safety – the summary measure is the total number of items reported. For the remaining domains, the summary measures are permanent income, having died by March 1, 2019, years of education, fair or poor health quality, and total assets. These summary measures are the primary basis for the results reported in Section 6, although results for the full set of 71 indicators are reported in the appendix.

5.2. Analytical Methods for Comparing Material Well-Being Across Poverty Measures

To empirically assess whether a poverty measure with or without a geographic adjustment better identifies a materially deprived population, we regress a measure of well-being on indicators for poverty status with and without a geographic adjustment, together with covariates reflecting characteristics of the sharing unit or its head. Using the sample of all sharing unit heads (and, for some mortality and health outcomes the sample of all individuals), we estimate:

$$\textit{Well-Being} = \alpha + \beta_1\, \textit{Geographic-Only Poor} + \beta_2\, \textit{Always Poor} + \beta_3\, \textit{Never Poor} + \boldsymbol{\lambda}'\boldsymbol{X} + \varepsilon, \qquad (3)$$

where *Geographic-Only Poor* is an indicator for being classified as poor with a geographic adjustment but not without, *Always Poor* is an indicator for being poor under both, and *Never Poor*

is an indicator for being non-poor under both. The reference group is therefore the non-geographic-only poor. Comparing the non-overlapping "switcher" groups (i.e., those added to and removed from poverty by a geographic adjustment) clarifies the analysis, since most individuals in poverty are unaffected by a geographic adjustment. $\boldsymbol{X}$ is a vector of characteristics of the sharing unit or its head, although we also show robustness to a more limited set of covariates.[12]

The main coefficient of interest is β_1, whose interpretation depends on how the outcome is coded. For outcomes on which higher values signify greater well-being (e.g., permanent income or appliances owned), $\beta_1 < 0$ indicates that the geographic-only poor are more disadvantaged than the non-geographic-only poor. For outcomes on which higher values signify greater deprivation (e.g., material hardships or mortality), $\beta_1 > 0$ indicates that the geographic-only poor are more disadvantaged. In either case, an estimate indicating that the geographic-only poor are more deprived implies that incorporating a geographic adjustment better identifies a deprived population. For binary outcomes, we estimate equation (3) using a probit model and calculate average partial effects over the geographic- and non-geographic-only poor subgroups.[13] For non-binary outcomes, we use a linear model. We report heteroskedastic-robust standard errors and use replicate weights to obtain standard errors accommodating complexities in the surveys' designs. We use individual survey weights corresponding to the sharing unit head multiplied by the number of individuals in the sharing unit.[14]

Table 2 reports the weighted shares of individuals and unweighted counts of individuals and sharing units for each of our four mutually exclusive and exhaustive poverty categories. Using the SPM in the CPS, 83.4% of individuals are never poor and 13.6% are always poor, leaving 1.5% in each switcher group. By construction the two switcher shares are the same, since poverty rates with and without an adjustment are both anchored to 15.1%. The switcher groups are larger in the SIPP (1.8% each using the SPM) and slightly smaller using the CIPM (1.4% in the CPS and 1.5% in the SIPP). Because most of our regressions are at the sharing unit level, the unit counts in

[12] The main set of covariates in $\boldsymbol{X}$ includes age, age-squared, an indicator for being female, an indicator for being married, an indicator for having a cohabiting partner, the number of adults in the sharing unit, the number of children in the sharing unit, indicators for race (i.e., dummies for White, Black, Asian, and other), a binary indicator for being Hispanic, and each of the race/ethnicity dummies interacted with being female.

[13] It is crucial to calculate average partial effects (APEs) over only the part of the overall sample that provides the relevant identifying variation. Otherwise, calculating APEs over the entire sample (including the always and never poor) may lead to unrepresentative estimates of APEs from the probit models (Curran, Meyer, and Wu 2026).

[14] For regressions at the individual level with mortality or health outcomes, we use individual survey weights, which are distinct from replicate weights. The former are designed to account for the sampling distribution of the survey while the latter are designed to simulate multiple samples from a given sample.

Columns 3 and 6 are relevant for precision. However, even the smallest cell (the geographic-only poor using the CIPM in the SIPP) contains 400 sharing units.

6. Main Regression Results

This section presents our main regression estimates that compare differences in well-being between poverty measures with and without a geographic adjustment. We walk through the SPM results in full, since the SPM is the measure that currently applies a geographic adjustment, and then show that the CIPM results hold and are sharpened in several cases.[15]

6.1. Estimates for the SPM

Table 3 reports estimates of β_1 from equation (3) for the fourteen summary measures, with Panel (a) using the SPM. Column 1 gives the point estimate (i.e., the coefficient for linear outcomes and the average partial effect for binary outcomes), and Column 2 provides the standard error. Columns 3 and 4 report the mean for the non-geographic-only poor (the reference group against which the coefficient should be evaluated) and the overall mean. Column 5 indicates whether the sign implies that a geographic adjustment identifies a more deprived population ("+") or a less deprived population ("–"). Figure 3, Panel (a) summarizes the sign and significance of all 71 individual indicators by domain, and Appendix Table A.1 reports estimates for each of them.

Beginning with permanent income, the geographic-only poor have $28,630 more in the CPS and $17,150 more in the SIPP, roughly 100% and 50% above the means for the non-geographic-only poor. Both differences are statistically significant at the 1% level. Low incomes therefore appear less permanent in high-cost areas, which is notable given the damaging effects of persistent poverty documented in prior work (see, e.g., Duncan and Rodgers 1991). The geographic-only poor also have 0.40 (3%) and 0.56 (5%) more years of education in the CPS and SIPP, again significant at the 1% level. Turning to mortality, where higher values signify greater deprivation, the geographic-only poor are 2.3 percentage points (18%) less likely to have died by 2019 in the CPS and 2.6 points (24%) less likely in the SIPP. However, neither estimate is statistically significant at conventional levels, as mortality is a relatively infrequent outcome.

[15] Even though the SPM analyses rely on survey information only, most cannot be produced using the public-use data. This is because the vast majority of our well-being indicators are found only in the SIPP, and geographic adjustment factors are at the CBSA level (which is identifiable only in the restricted-use SIPP and not the public-use SIPP).

Turning from mortality to self-reported health problems more generally, the differences are larger and more precisely estimated. The geographic-only poor are 6.0 percentage points (27%) less likely to report poor or fair health quality in the CPS and 7.1 percentage points (39%) less likely in the SIPP, with both estimates significant at the 1% level.

The geographic-only poor also report 0.16 (13%) fewer material hardships and 0.12 (33%) fewer home quality problems, with the latter significant at the 10% level. Appliances comprise the one summary measure suggesting that a geographic adjustment identifies a more deprived population. The geographic-only poor own 0.19 (3%) fewer appliances, although the estimate is small and imprecise, and the difference is driven by lower ownership of air conditioning, washers, and dryers (Appendix Table A1). This may in part reflect where the groups reside, as the geographic-only poor tend to be located in California and the Northeast while the non-geographic-only poor are concentrated in the Deep South. The former regions are likely to be cooler (reducing the need for air conditioning) and denser (reducing the prevalence of in-unit washers and dryers).[16] Appendix Table A3 supports this interpretation, showing that controlling for county-level average monthly temperatures and the proportion of single-family homes leaves the geographic-only poor owning more total appliances (though insignificantly) in Panel (a). Furthermore, the estimates for air conditioning and dryer are no longer significant after including these controls.

Turning to assets, the geographic-only poor have $96,560 (116%) more total wealth, with this difference significant at the 1% level. As reported in Appendix Table A1, this comprises $31,920 (79%) more home equity, $1,279 (34%) more vehicle equity, and $63,370 (163%) more in other assets such as bank accounts, retirement accounts, and stocks and bonds. The difference in net worth is not statistically significant, since the geographic-only poor also carry significantly more debt. However, higher debt need not indicate greater disadvantage, as it reflects the ability to borrow and thereby to consume. Finally, the geographic-only poor report 0.18 (17%) fewer food security problems and 0.03 (3%) fewer public services and safety problems, although neither estimate is statistically significant.

The individual indicators behind these summary measures point the same way, as shown in Panel (a) of Figure 3. Within every domain except appliances, a majority of indicators favor the geographic-only poor being less deprived, even though many are individually imprecise. The

[16] Consistent with this, Murphy (2025) finds that households in denser neighborhoods and smaller homes spend considerably less on durables and utilities conditional on income.

indicators pointing the other way are concentrated in appliances and in public services and safety. As with appliances, several of the latter plausibly reflect urban location rather than deprivation, since the two statistically significant estimates (staying home for safety and taking someone along when going out) describe behaviors more common in denser areas. In summary, incorporating a geographic adjustment to SPM thresholds identifies a less deprived poor population than those who are otherwise poor without one. This holds for 13 of the 14 summary measures and 55 of the 71 individual indicators, with estimates statistically significant for 8 summary measures and 24 individual outcomes. In other words, low-income individuals in lower-cost areas broadly appear to be more disadvantaged than those in higher-cost areas.

Yet, a caveat of these results is that the SPM may classify some individuals with high levels of well-being as poor, since it relies on survey-reported incomes that are subject to underreporting and does not explicitly account for the flow value of assets. We therefore also examine results using the CIPM, which corrects for misreporting using administrative data and incorporates the income flow from assets.

6.2. Estimates for the CIPM

Panel (b) of Table 3 reports the corresponding CIPM estimates, with Figure 3b and Appendix Table A2 showing estimates for the individual indicators. A geographic adjustment again appears to identify a less deprived poor population. The estimates are in several cases sharper, with ten of fourteen summary measures statistically significant under the CIPM compared with eight under the SPM.

The geographic-only poor have $24,140 (99%) more permanent income in the CPS and $17,800 (72%) more in the SIPP, both significant at the 1% level. They also have 0.57 (5%) and 0.70 (6%) more years of education, significant at the 1% and 5% levels, in the CPS and SIPP. When it comes to mortality, the estimates differ between the two surveys. In the CPS, the geographic-only poor are 2.5 percentage points (23%) less likely to have died by 2019, an estimate now significant at the 5% level where its SPM analog was not. In the SIPP, the estimate reverses sign, with the geographic-only poor 2.1 points (24%) more likely to have died, although this remains statistically insignificant. Differences in self-reported health remain significant in both

surveys, with the geographic-only poor being 6.8 and 3.7 percentage points less likely to report poor or fair health quality in the CPS and SIPP, respectively.

The geographic-only poor also report 0.18 (14%) fewer total material hardships, again statistically insignificant, and 0.16 (38%) fewer total home quality problems, now significant at the 5% rather than the 10% level. Appliances again point the other way, with the geographic-only poor having 0.23 (4%) fewer total appliances. As under the SPM, this difference is driven by lower ownership of air conditioning units, washers, and dryers, and it reverses once county temperature and the share of single-family homes are controlled for. The geographic-only poor continue to have more assets, holding $61,530 (211%) more total wealth than the non-geographic-only poor. Finally, the geographic-only poor report 0.211 (22%) fewer total food security problems, now significant at the 10% level where the SPM estimate was not significant, and 0.07 (5%) fewer public services and safety problems, which remains insignificant.

Overall, the CIPM again identifies a less deprived poor population under a geographic adjustment for 12 of the 14 summary indicators and 55 of the 70 individual indicators, with estimates statistically significant for 10 summary measures and 24 individual measures. Figure 3, Panel (b) shows a similar consistency between the summary measures and their underlying indicators as under the SPM. That these patterns hold under a broader and more accurate income measure – one that corrects for underreporting and incorporates asset flows – suggests that they are not driven simply by mismeasurement of resources at the bottom of the distribution.

7. Extensions and Robustness Checks

In this section, we present a series of extensions and robustness checks, reporting results for the fourteen summary measures. These include scaling the geographic adjustment factor, using Regional Price Parities as an alternative price index, extending the analysis to deep and near poverty, using the OPM as the poverty measure, and varying the covariates in our specifications. We focus on the CIPM throughout, as it measures income most accurately; results using the SPM point in the same direction and appear in the appendix. Figure 5 summarizes the results across all of these specifications except the scaling exercise and OPM, and Appendix Figure A4 shows the analog of this figure using the SPM and OPM.

7.1. Scaling the Geographic Adjustment Factor

If areas with higher median rents also have higher amenities, then a full adjustment for geographic differences in rents will over-adjust thresholds for geographic differences in well-being more broadly. Because there is no commonly accepted methodology for moderating the adjustment to account for amenities, we explore a range of weights. Specifically, we scale the geographic adjustment factor by fractions ranging from 0.1 to 1, where 0 corresponds to no adjustment and 1 to the full adjustment underlying our main results. Renwick (2018) provides the closest analog, using a single scaling of 0.5 to reduce the geographic adjustment.

Intuitively, scaling compresses the geographic adjustment factor for each area toward 1, shrinking the gap between high- and low-cost areas while leaving the national average unchanged. For example, if the full adjustment factors for two areas are 1.5 and 0.6, then applying a 0.5 scaling moves them to 1.25 and 0.8. We then multiply these scaled factors by the base threshold and equivalence scale to obtain revised poverty thresholds (corresponding to different scalings of the geographic adjustment). We continue to anchor poverty rates at 15.1%. An implication of a lower fraction is that fewer observations switch in or out of poverty as a result of applying a geographic adjustment. We therefore focus on permanent income and years of education, which are available in both the CPS and SIPP and have substantial variation to allow for greater statistical power.

Figure 4 shows estimates of the coefficient on being geographic-only CIPM poor across various fractions of the MRI variation applied to the CIPM poverty threshold. For each outcome, the solid circles reflect estimates from the CPS and the hollow triangles reflect estimates from the SIPP (surrounded by 95% confidence bands). The confidence bands widen (i.e., standard errors are larger) at lower fractions, where fewer observations fall into either switcher group. The point estimates for permanent income in Panel (a) and years of education in Panel (b) are positive across the entire range in both surveys, with the sole exception of the statistically insignificant estimate for years of education in the CPS at a 0.1 scaling. Thus, even a partial adjustment for geographic differences in rental costs appears to identify a poor population that is less deprived. The point estimates fall in a fairly tight range between scalings of 0.5 and 1.0. For permanent income, the coefficients range from $24,140 to $28,330 in the CPS and $14,600 to $18,420 in the SIPP. For years of education, they range from 0.52 to 0.73 in the CPS and from 0.54 to 0.70 in the SIPP. Appendix Figure A2 shows the corresponding SPM results.

7.2. Using Regional Price Parities Rather Than the MRI Price Index

We next assess substitute Regional Price Parities (RPPs) for the MRI, described in Section 3.3, to assess whether adjusting for prices across a broader bundle of goods changes our conclusion about whether a geographic adjustment identifies a less deprived poor population.[17] We obtain RPP values from the BEA for calendar year 2010 by metropolitan area and – for areas outside a specified metropolitan area – for "all other metropolitan areas" and "non-metropolitan areas" within a state. We assign each individual the RPP matching their survey-identified place of living. Because RPPs are defined such that the national average is 1, they serve as the full adjustment factor, and the adjusted poverty threshold is simply the base threshold multiplied by the equivalence scale and the RPP. Panel (a) of Appendix Table A5 shows that the switcher shares under the RPP adjustment (1.45% in the CPS and 1.51% in the SIPP) are comparable to the original shares under the MRI adjustment (1.43% in the CPS and 1.46% in the SIPP).[18]

Panel (b) of Appendix Table A6 reports the estimates. Thirteen of the fourteen summary measures point toward a less deprived population identified by a geographic RPP adjustment, with ten of the thirteen estimates statistically significant at the 10% level. As under the MRI, the only measure pointing the other way is the number of appliances, which as discussed above likely reflects the location-specific needs of the non-geographic-only poor. These estimates are comparable to their counterparts using the MRI in Table 3, although the estimates for material hardships and food security are significant under the RPP adjustment but not the MRI, while the estimate for home quality is significant under the MRI but not the RPP. In sum, these results show that adjusting for price differences across a broader bundle of goods does not change our central finding that a geographic adjustment identifies a less deprived poor population. Furthermore, the consistency of the results using the RPP and MRI adjustments suggests that an intermediate index such as the Food, Apparel, and Rent RPP (which covers a set of goods strictly between those covered in the MRI and RPP) would yield similar results.

[17] The RPP adjustment also decreases poverty rates in rural areas (e.g., Midwest and Deep South) and increases poverty rates in urban areas (e.g., New England, mid-Atlantic, and California) (Appendix Figure A1). While the MRI and RPP adjustments move poverty rates in the same direction in most of the country, there are a few areas where they diverge. Specifically, the RPP adjustment increases poverty while the MRI adjustment decreases poverty in more remote areas (e.g., rural California and Indiana) where housing costs are lower but the costs of other goods are higher. In contrast, the RPP adjustment decreases poverty while the MRI adjustment increases poverty in coastal areas (e.g., parts of Florida, South Carolina, Delaware, etc.) where housing costs are higher but the costs of other goods are lower.

[18] Panel (a) of Appendix Table A4 shows the analogous numbers using the SPM.

7.3. Deep and Near Poverty

We next examine whether a geographic adjustment using the MRI identifies a less deprived population among the deep poor (incomes below 50% of the poverty line) or the near poor (with incomes below 150% of the poverty line). We follow the same methodology as for regular poverty, with the only difference being that we anchor deep poverty rates to 6.7% and near poverty rates to 24.6%. These rates are based on the deep and near poverty rates calculated in the CPS (using survey-reported pre-tax money income and OPM thresholds) for 2010. Panels (b) and (c) of Appendix Table A5 report the switcher shares, which range from 0.64% to 0.66% for deep poverty and 1.84% to 2.10% for near poverty under the CIPM.[19]

Appendix Table A7 reports the deep poverty estimates. A geographic adjustment identifies a less deprived population in deep poverty for thirteen of the fourteen outcomes, with seven significant at the 10% level. The only outcome (material hardships) that points in the other direction is statistically insignificant. The mortality estimates are particularly notable, with the geographic-only deep poor 40% and 50% less likely in the CPS and SIPP to have a head die by 2019 than the non-geographic-only deep poor, both significant at the 5% level or better. The estimates are striking because mortality is a tail event and the non-geographic-only deep poor (particularly those in the Deep South) may be especially prone to suffer from health problems carrying elevated mortality risk. Appendix Table A8 reports the near poverty estimates, where a geographic adjustment continues to identify a less deprived population for eleven of the fourteen summary measures, with five significant at the 10% level. As a result, our central finding extends to other cutoffs.

7.4. Alternative Poverty Measures and Specifications

In this final subsection, we describe a series of additional extensions and robustness checks. We start by examining the effects of geographic adjustments using the OPM. Although the OPM has well-known limitations, it is also the poverty measure conceptually closest to what government programs like SNAP and Head Start use to determine benefit eligibility.[20] Appendix

[19] Panels (b) and (c) of Appendix Table A4 shows the analogous numbers using the SPM.

[20] Like the SPM, the OPM relies exclusively on survey-reported income. Unlike the SPM, the OPM uses pre-tax money income as its resource measure, uses the survey family (containing only related individuals) as its resource unit, and relies on poverty thresholds that vary by family size and the number of related children and do not feature geographic adjustments. To incorporate geographic adjustments, we multiply the OPM thresholds by the geographic adjustment factor embedded in equation (2).

Table A9 shows that a geographic adjustment identifies a less deprived population for twelve of the fourteen summary measures, with five significant at the 10% level. Moreover, the two summary outcomes (number of appliances and number of public services and safety problems) that point in the opposite direction are statistically insignificant.

We next examine the sensitivity of our results to the covariates in equation (3). Re-estimating our regressions with the most parsimonious set of covariates possible, we find that a geographic adjustment identifies a less deprived population in poverty for nine of the fourteen summary measures, with five significant at the 10% level (Appendix Table A10).[21] Years of education is the domain where the result weakens the most, reversing sign in both surveys though insignificantly in each. One reason may be that we no longer control for Hispanic status, and Hispanics tend to have less education and are over-represented among the geographic-only poor.

Finally, we add binary indicators for geographic region (Northeast, Midwest, South, West) or an indicator for rural status to our main set of controls. Controlling for region barely changes our results, in which a geographic adjustment continues to identify a less deprived population in poverty for twelve of the fourteen summary measures, with nine statistically significant at the 10% level (Appendix Table A11). In contrast, controlling for rural status weakens our results, leaving eleven summary outcomes pointing toward a less deprived poor population, with five statistically significant at the 10% level (Appendix Table A12). In summary, the urban versus rural distinction between the geographic-only and non-geographic-only poor appears to be a key driver of our results, whereas differences across versus within geographic regions matter little.

8. Why Are the Poor Better Off in Higher-Cost Areas?

This section provides empirical explanations for the overarching result that those who are poor in higher-cost areas appear less deprived than those who are poor in lower-cost areas. Intuitively, this must arise out of the idea that higher prices in certain areas are correlated with greater provision of other things valued by the poor. We test this hypothesis by estimating the correlation of local hourly wages, non-labor income, and public spending with local prices. These

[21] This entails controlling for age when examining permanent income, education, and mortality (as these outcomes are mechanically correlated with age), unit size when examining material hardships, home quality problems, appliances, food security problems, and public services (as these outcomes are asked of anyone in the household), and age and unit size when examining assets (as they are mechanically correlated with age and are not equivalized by unit size or composition). Importantly, we no longer control for gender, marital status, unit type, or race/ethnicity.

analyses are exploratory, but they provide further evidence that it is highly complicated – if not impossible – to calibrate precisely how local amenities and incomes adjust with local prices.

Panel (a) of Table 4 reports the coefficients from CBSA-level regressions of the log of various income sources on the log of local prices calculated using either the MRI or RPP.[22] Hourly wages, calculated for non-elderly adults with a high school diploma or less, increase by 0.87% and 1.07% given a 1% increase in the MRI and RPP, with both elasticities significant at the 1% level. Wages in the low-wage labor market therefore rise nearly one for one with local prices. Turning to non-labor income, Social Security retirement income increases by 0.30% and 0.40%, and pension income by 1.37% and 1.38%, given a 1% increase in the MRI and RPP. Housing assistance is also significantly positively correlated with prices, increasing by 3.6% and 3.3% given a 1% increase in the MRI and RPP. That these elasticities are so far above one suggests the relationship between housing assistance and median rents is not purely mechanical. There are also transfers (Social Security disability income, SNAP, and SSI) whose per-capita amounts are negatively correlated with prices, although the SSI elasticities are not statistically significant.

Panel (b) reports elasticities of per-capita state and local spending with respect to the MRI or RPP.[23] Many of these categories (e.g., education, police, environment, etc.) can be interpreted as spending on amenities. For the majority of categories (including welfare, K-12 education, police, environment and housing, and other spending), the elasticities are significantly positive and above unity. The elasticities for higher education and health/hospital spending are negative though statistically insignificant, so overall education spending (which combines K-12 and higher education) remains significantly positive but below unity. Taken together, the results in Table 4 indicate that wages, various sources of non-labor income, and most state and local spending categories are positively correlated with prices. The results using the MRI and RPP are very similar, and the elasticities in many cases are above one. Places with higher prices thus tend to have higher wages and greater provision of public goods, which helps to rationalize the finding that a geographic adjustment for local price differences identifies a less deprived poor population.

[22] Average incomes are calculated using the CPS ASEC for reference year 2010, and the MRI and RPP are also calculated for 2010. To make the MRI and RPP elasticities comparable, we scale the MRI by 38.2% (which is the housing share of consumption found using the CE Survey).

[23] Specifically, Panel (b) shows coefficients from state-level regressions of the log of various spending amounts on the log of local prices calculated using either the MRI or RPP. We calculate these elasticities for calendar year 2012 because the spending measures are derived from a report containing 2012 values (Gordon, Auxier, and Iselin 2016). As a result, we correspondingly use MRI and RPP values calculated for calendar year 2012. The MRI values in Panel (b) are scaled similarly as those in Panel (a) to make the MRI and RPP elasticities comparable.

Appendix Table A13 further shows that measures of intergenerational mobility are positively and strongly correlated with local median rent levels. The mobility outcomes are drawn from the Opportunity Atlas (Chetty et al. 2018) and comprise household and individual incomes at age 35 for those born between 1978 and 1983, conditional on parental income at the 25th percentile.[24] The association is positive and significant at every level of geography we examine. Higher-price areas therefore appear to offer not only higher current incomes and greater amenities, but also better long-run prospects for children growing up in them.

9. Conclusions

In this paper, we assess whether geographically adjusting poverty thresholds for cost-of-living differences identifies a more deprived population, and we find that it does not. For nine of the ten domains of well-being we examine, the summary measure indicates that those classified as poor with a geographic adjustment (who disproportionately live in urban areas) are better off than those classified as poor without one (who disproportionately live in rural areas). This holds for three separate poverty measures (SPM, CIPM, and OPM) across two surveys (CPS and SIPP), and it survives partial adjustments that scale the geographic adjustment factor to crudely account for amenities, Regional Price Parities as an alternative index, deep and near poverty thresholds, and alternative sets of covariates. In short, the preponderance of evidence suggests that incorporating a geographic adjustment runs counter to a central objective of a poverty measure: identifying the least advantaged population.

The explanation for this result is that local prices capitalize much of what makes a place desirable. Wages in the low-wage labor market rise nearly one for one with local prices, per-capita state and local spending on welfare, K-12 education, police, and environment and housing rises more than one for one, and children raised in higher-price areas go on to earn substantially more as adults. Higher prices in local areas are therefore at least partly offset by higher wages and greater public provision, so raising thresholds where prices are high draws in a less deprived population while excluding a more deprived one elsewhere.

These findings bear directly on program targeting. Poverty thresholds underpin eligibility for key transfer programs such as SNAP and Medicaid, while poverty rates determine the

[24] The median rent levels for more granular geographic units (tracts, counties, and community zones) are obtained for 2012-16 from the Opportunity Atlas, and the median rent levels for CBSAs are calculated for 2008-10 using the CPS.

geographic allocation of federal funds through Title I and other place-based programs. A geographic adjustment raises measured poverty in expensive metropolitan areas and lowers it across the rural South, Appalachia, and the Midwest, shifting both benefits and funding toward places where the poor are – on most of the margins we can measure – better off. Proposals to incorporate cost-of-living differences into official poverty statistics have come from a wide range of stakeholders and have been implemented by the Census Bureau in its SPM. Our results suggest that such adjustments would weaken the ability of programs to reach the most disadvantaged. The same caution applies to broader efforts by governments and other entities to vary grants and subsidies across locations on the basis of local prices.

Future researchers might consider using more years of data to increase the statistical power of the estimates and examine if our results generalize to other time periods. However, the gains to statistical power are limited in the SIPP, where the panel structure means observations are not independent over time within a panel. The fine geography available in the surveys would also permit linking individuals to tract-level measures of well-being, including intergenerational mobility, air quality, and access to local services, allowing us to compare these outcomes between those classified as poor with and without a geographic adjustment. More broadly, the set of well-being indicators we assemble – building upon those used in Meyer et al. (2021) – can be used to evaluate the suitability of modifications to a poverty measure, such as incorporating in-kind transfers and asset flows into the resource measure. More broadly, these well-being indicators open the door to a variety of questions about how policies identify and reach the disadvantaged, including how well government programs target those they are meant to serve.

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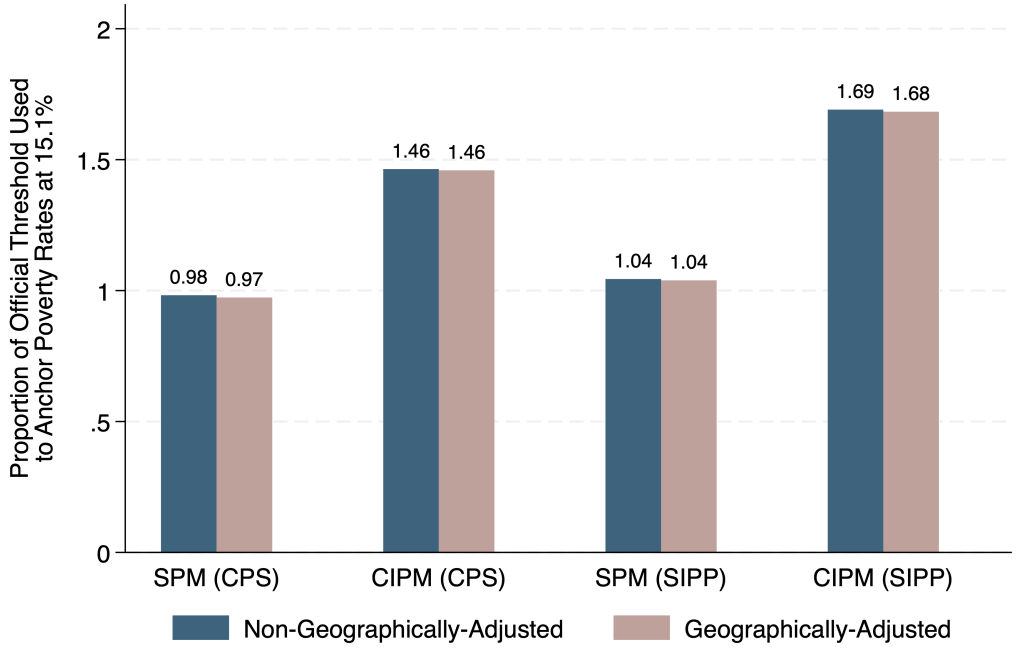
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Figures and Tables

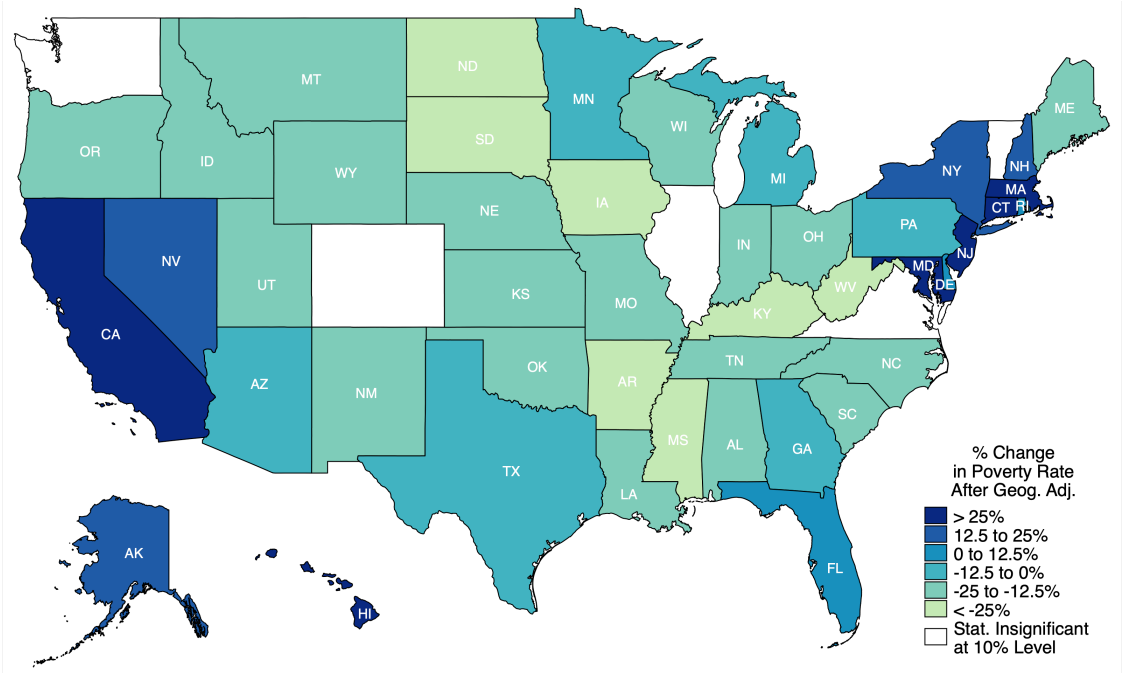
Figure 1. Scaling Factors Used to Anchor Poverty Rates at Official Levels



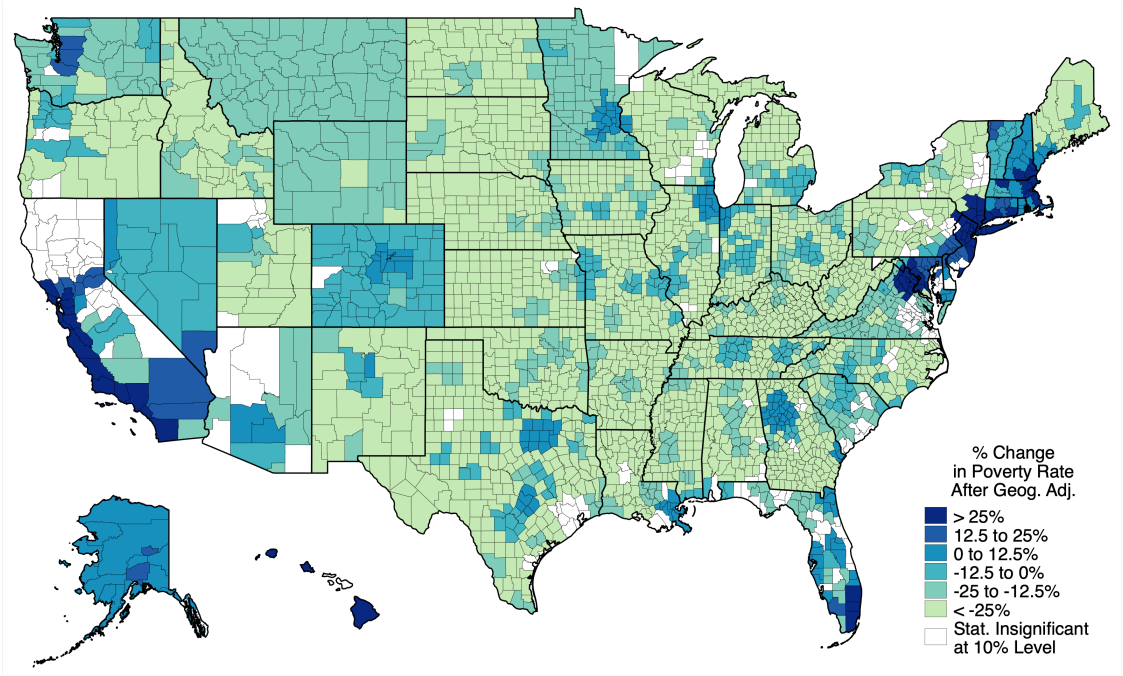
Data: 2011 CPS ASEC (public-use)
Notes: This figure shows the fixed factors by which the SPM and CIPM thresholds are scaled in both the CPS and SIPP so that all poverty rates are anchored to 15.1%, which was the official poverty rate in 2010.

Figure 2. Map of Percent Changes in SPM Poverty Rates After Geographic Adjustments

(a) By State



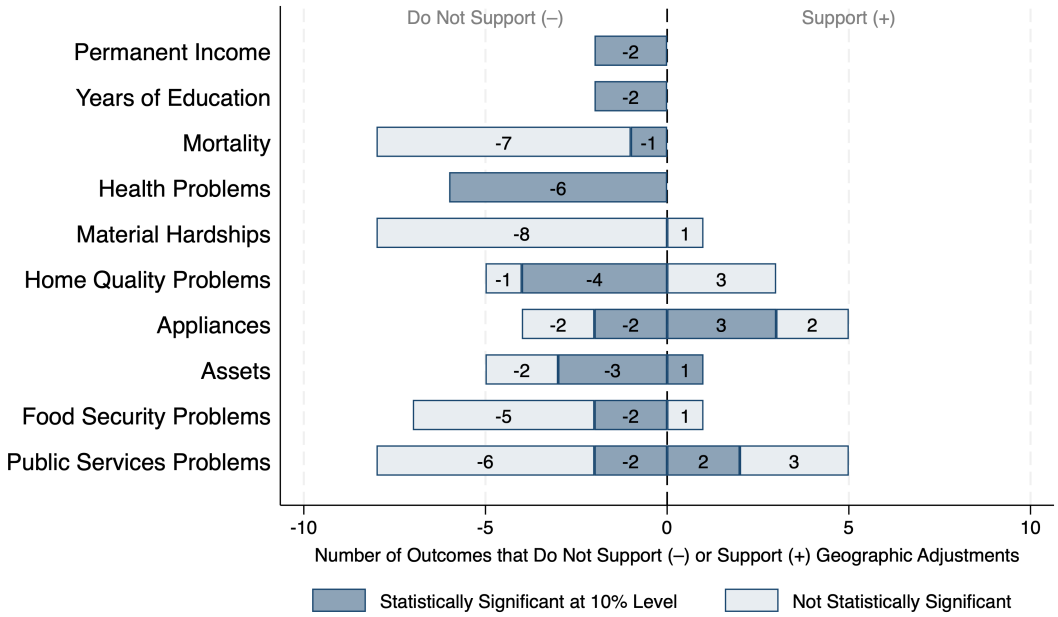
(b) By CBSA



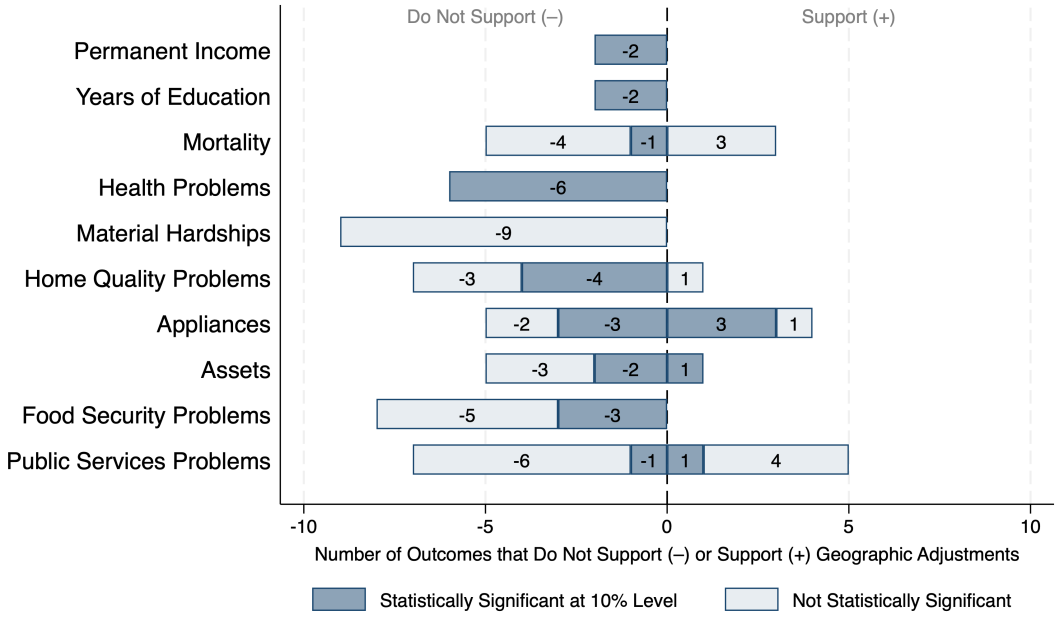
Data: 2010-2012 CPS ASEC (public-use)
Notes: These maps show differences in SPM poverty rates by state and CBSA before and after geographic adjustments (where the national poverty rates are anchored to 15.1%). The percent change is calculated relative to a base rate without geographic adjustments. In Panel (b), we use a county-level template but calculate rates by CBSA and assign them to all counties within that CBSA. For areas outside of CBSAs, we calculate rates for "non-metro" and "other metro" and apply to all counties in those areas. Following Census Bureau standards, these sub-state estimates are averaged over three years of the CPS ASEC (covering reference years 2009-2011).

Figure 3. Number of Well-Being Outcomes Supporting or Not Supporting Geographic Adjustments

(a) Using Supplemental Poverty Measure (SPM)



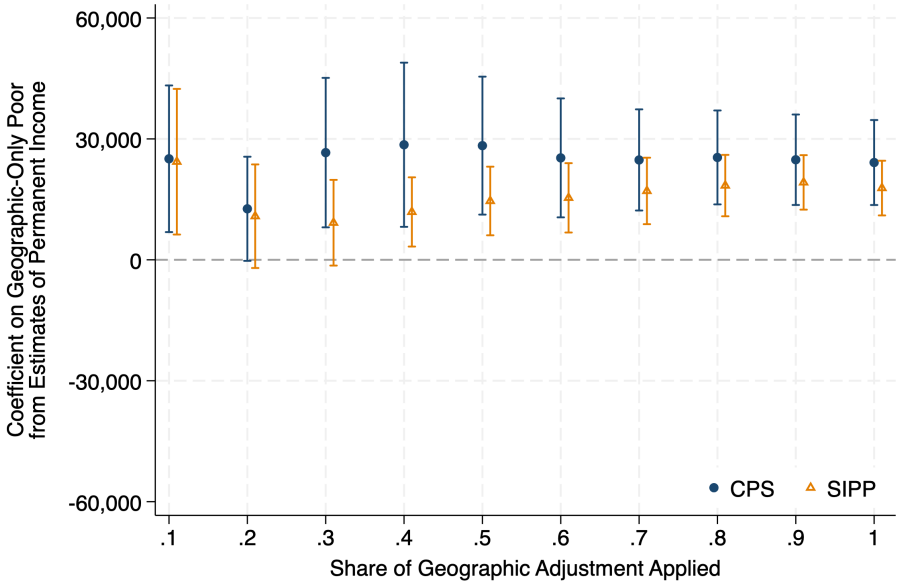
(b) Using Comprehensive Income Poverty Measure (CIPM)



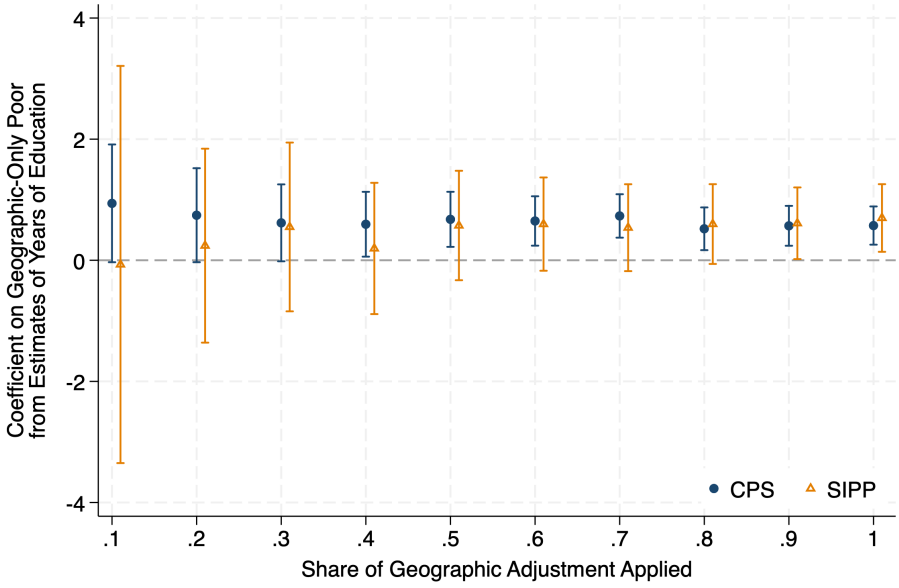
Data: 2010-2012 CPS ASEC (public-use)
Notes: This figure shows the number of well-being outcomes (71 in total, separately across ten domains) for which a geographic adjustment identifies a more deprived population, using the SPM in Panel (a) and CIPM in Panel (b). Estimates are based on the sign and significance of β_1 in Equation (5), which is the coefficient on an indicator for being geographic-only poor (vs. non-geographic-only poor). Sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS) for most outcomes, except for some of the mortality and health outcomes (which are at the individual level).

Figure 4. Effects of Partial Geographic Adjustments on Characteristics of the Poor (CIPM)

(a) Permanent Income

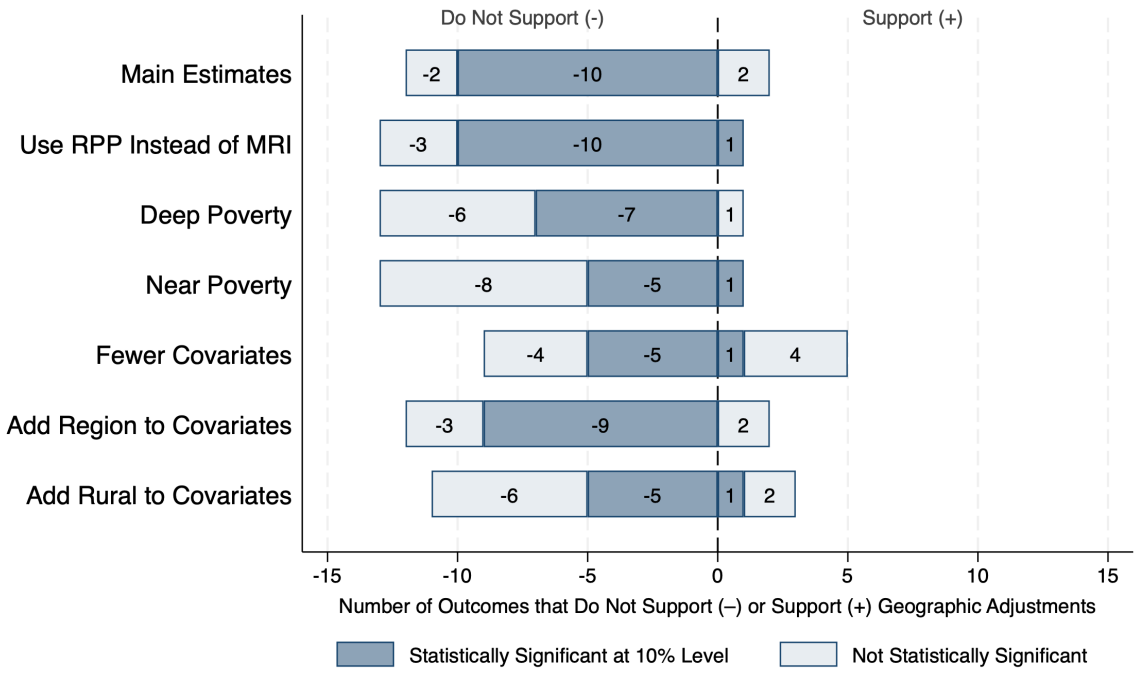


(b) Years of Education



Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: These figures report coefficients on an indicator for being geographic-only CIPM poor (vs. non-geographic-only CIPM poor) from regressions of permanent income and years of education on geographic poverty categories and covariates. Across estimates, the geographic adjustment factor is scaled from 0.1 to 1.0, where 1.0 corresponds to the full geographic adjustment. The sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS). Confidence bands are at the 95% level.

Figure 5. Number of Summary Outcomes Supporting or Not Supporting Geographic Adjustments Across Specifications (CIPM)



Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This figure shows the number of summary outcomes (out of 14) for which a geographic adjustment identifies a more deprived population, using the CIPM and across various specifications. Outcome domains include mortality, permanent income, education, and health problems (in CPS and SIPP), and appliances, assets, food security problems, home quality problems, material hardships, and public services problems (in SIPP only).

Table 1. Poverty Rates (%) and Changes from Geographic Adjustments

Characteristic	Supplemental Poverty Measure (SPM)				Comprehensive Income Poverty Measure (CIPM)			
	CPS		SIPP		CPS		SIPP	
	Poverty Rate (No Geog. Adj.) (1)	Change from Geog. Adj. (2)	Poverty Rate (No Geog. Adj.) (3)	Change from Geog. Adj. (4)	Poverty Rate (No Geog. Adj.) (5)	Change from Geog. Adj. (6)	Poverty Rate (No Geog. Adj.) (7)	Change from Geog. Adj. (8)
Rural	13.96	-2.56***	19.96	-5.65***	14.41	-2.59***	18.98	-4.55***
Census Division								
New England	9.54	2.14***	10.75	1.25***	8.56	1.96***	9.14	1.95***
Mid-Atlantic	13.10	1.28***	11.62	1.79***	12.57	1.93***	12.66	0.81***
East North Central	14.63	-1.21***	14.72	-2.63***	14.30	-1.38***	15.54	-1.85***
West North Central	12.33	-2.30***	13.31	-3.03***	12.84	-1.90***	11.61	-1.98***
South Atlantic	16.31	-0.44**	16.84	-0.66***	15.76	-0.16	14.98	0.10
East South Central	18.71	-4.49***	21.65	-3.68***	20.20	-5.39***	19.77	-3.77***
West South Central	17.63	-2.01***	17.17	-2.50***	18.02	-1.94***	17.47	-1.84***
Mountain	15.54	-0.67***	16.04	-0.97**	16.43	-0.72***	16.99	-0.45
Pacific	15.11	4.33***	13.93	6.25***	15.18	3.89***	15.73	4.17***
Race/Ethnicity of Head								
White	13.62	-0.08	13.89	0.02	13.83	-0.21**	13.60	-0.18
Black	24.22	-0.46	21.49	-0.56*	22.59	0.40	23.66	0.59
Asian	13.05	2.42***	14.44	2.78***	14.01	2.51***	13.48	2.34***
Other Race	20.04	0.44	21.18	-1.49*	19.90	0.12	21.41	-0.70
Hispanic	24.43	2.44***	22.49	3.92***	24.15	2.27***	27.28	3.40***
Unit Type								
Elderly	15.77	-0.37*	14.05	-0.61**	11.98	-0.58***	10.27	-0.55**
Single Parent	32.67	-1.24***	34.68	-1.87**	37.26	-0.69*	41.19	-0.28
Multiple Parents	12.98	0.40***	13.05	0.50*	14.26	0.34**	14.85	0.40
Single Childless	25.89	-0.25	26.97	-0.11	25.66	-0.08	27.02	-0.41**
Multiple Childless	10.02	-0.07	10.08	-0.04	8.81	-0.08	7.44	-0.19
Observations	205,000	205,000	88,000	88,000	170,000	170,000	85,000	85,000

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table shows poverty rates (without geographic adjustments) and the change in poverty rates from incorporating geographic adjustments. For Columns (1)-(4), the sample consists of all individuals, weighted using individual survey weights. For Columns (5)-(8), the sample consists of individuals in PIKed sharing units (and, additionally in the CPS, no whole imputes), weighted using individual survey weights adjusted for non-PIKing at the sharing unit level (and additionally for whole imputes in the CPS).

Table 2. Shares and Counts by Geographic Poverty Category

Poverty Category	CPS Weighted Share of Inds. (1)	CPS Sample Size (Inds.) (2)	CPS Sample Size (Fams.) (3)	SIPP Weighted Share of Inds. (4)	SIPP Sample Size (Inds.) (5)	SIPP Sample Size (Fams.) (6)
A. Supplemental Poverty Measure (SPM)						
Never Poor	0.8338	173,000	65,000	0.8307	73,000	29,000
Non-Geographic-Only Poor	0.0152	3,100	1,300	0.0183	1,800	750
Geographic-Only Poor	0.0152	3,300	1,200	0.0183	1,500	500
Always Poor	0.1358	26,000	11,500	0.1327	12,000	5,500
B. Comprehensive Income Poverty Measure (CIPM)						
Never Poor	0.8346	163,000	60,500	0.8344	71,500	28,500
Non-Geographic-Only Poor	0.0143	2,800	1,100	0.0146	1,400	550
Geographic-Only Poor	0.0143	2,800	950	0.0146	1,100	400
Always Poor	0.1367	24,000	9,800	0.1365	11,500	4,800

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table shows the weighted share of individuals and the unweighted number of individuals and sharing units in each of our four geographic poverty categories for the SPM and CIPM in both the CPS and SIPP. "Never Poor" is not poor with or without geographic adjustments. "Non-Geographic-Only Poor" is poor under no geographic adjustments and not poor under geographic adjustments. "Geographic-Only Poor" is poor under geographic adjustments and not poor under no geographic adjustments. "Always Poor" is poor with and without geographic adjustments. Poverty rates are anchored to 15.1%, which is the official rate in the CPS. The sample for the SPM estimates consists of all individuals, weighted using original survey weights. The sample for the CIPM estimates in the CPS consists of all individuals in sharing units where at least one member has a PIK and no member is whole imputed, weighted using individual survey weights adjusted for non-PIKing and whole imputes (at the sharing unit level). The sample for the CIPM estimates in the SIPP consists of all individuals in sharing units where at least one member has a PIK, weighted using individual survey weights adjusted for non-PIKing (at the sharing unit level).

Table 3. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/–) (5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	28,630***	(6,278)	26,980	98,620	–
Permanent Income (*SIPP*)	17,150***	(3,819)	33,870	92,930	–
Years of Education (*CPS*)	0.4000***	(0.1410)	11.840	13.640	–
Years of Education (*SIPP*)	0.5630***	(0.2270)	12.060	13.700	–
Head Died by 2019 (*CPS*)	-0.0226	(0.0140)	0.124	0.071	–
Head Died by 2019 (*SIPP*)	-0.0259	(0.0165)	0.110	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0603***	(0.0137)	0.226	0.118	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0711***	(0.0148)	0.182	0.103	–
Number of Material Hardships (*SIPP*)	-0.1550	(0.1370)	1.164	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.1230*	(0.0654)	0.370	0.224	–
Number of Appliances (*SIPP*)	-0.1900	(0.1660)	6.207	6.988	+
Total Wealth (*SIPP*)	96,560**	(44,810)	82,930	384,900	–
Number of Food Security Problems (*SIPP*)	-0.1750	(0.1220)	1.022	0.460	–
Number of Public Service Problems (*SIPP*)	-0.0298	(0.1300)	1.165	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	24,140***	(5,377)	24,430	98,090	–
Permanent Income (*SIPP*)	17,800***	(3,461)	24,850	92,930	–
Years of Education (*CPS*)	0.5730***	(0.1610)	11.750	13.630	–
Years of Education (*SIPP*)	0.6980**	(0.2850)	11.930	13.700	–
Head Died by 2019 (*CPS*)	-0.0247**	(0.0116)	0.109	0.071	–
Head Died by 2019 (*SIPP*)	0.0209	(0.0220)	0.088	0.080	+
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0683***	(0.0147)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0372**	(0.0142)	0.181	0.104	–
Number of Material Hardships (*SIPP*)	-0.1830	(0.1510)	1.280	0.645	–
Number of Home Quality Problems (*SIPP*)	-0.1560**	(0.0747)	0.410	0.225	–
Number of Appliances (*SIPP*)	-0.2300	(0.1620)	6.273	6.992	+
Total Wealth (*SIPP*)	61,530**	(24,980)	29,120	386,300	–
Number of Food Security Problems (*SIPP*)	-0.2110*	(0.1280)	0.948	0.459	–
Number of Public Service Problems (*SIPP*)	-0.0694	(0.1390)	1.332	0.950	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. Panel (a) relies on the SPM and Panel (b) relies on the CIPM. The sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS) for most outcomes, except for some of the mortality and health outcomes (which are at the individual level). For most outcomes, sample sizes are 64,500 and 34,000 in the CPS and SIPP, respectively; for head mortality, it is 63,500 and 33,000 in the CPS and SIPP; for individual heath, it is 85,000 in the SIPP; for assets, it is 33,500 in the SIPP. Probit APEs are reported for binary outcomes. Robust standard errors are in parentheses and are calculated using replicate weights.

Table 4. Elasticities of Income and Spending Amounts with Respect to Price Indices

Outcome	Elasticity of Outcome With Respect to MRI (1)	Elasticity of Outcome With Respect to RPP (2)
	A. Wage and Non-Wage Income Sources	
Hourly Wage (per person 18-64 with HS or less)	0.874***	1.072***
Social Security Retirement Income (per person 62+)	0.296**	0.396***
Social Security Disability Income (per capita)	-2.173***	-2.151***
Pension Income (per person 60+)	1.369***	1.381***
SNAP (per capita)	-2.461***	-2.972***
Housing Assistance (per capita)	3.643***	3.304***
SSI (per capita)	-0.252	-0.452
Observations	341	341
Unit of Analysis	CBSA	CBSA
	B. Per-Capita State Spending	
Welfare	1.200**	1.256**
All Education	0.671**	0.840***
K-12 Education	1.206**	1.363***
Higher Education	-1.040	-0.852
Health and Hospitals	-0.591	-0.668
Police	1.800***	1.901***
Environment, Housing	1.773***	1.937***
Other Spending	3.716***	3.871***
Observations	51	51
Unit of Analysis	State	State

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC (public-use), Gordon, Auxier, and Iselin (2016) for spending measures, MRI and RPP values (2010, 2012)

Notes: Panel (a) shows the coefficients from regressions of the natural log of various income sources on the natural log of local prices calculated using either the MRI or the RPP. For wages, we use the 2011 CPS ASEC for individuals ages 18-64 with a high school degree or less and weight the average using survey weights. We calculate per capita outcomes as the weighted total of an outcome divided by the weighted population. Housing assistance is drawn from the Census Bureau's SPM Research File. Both the MRI and RPP are calculated for calendar year 2010. Panel (b) shows the coefficients from regressions of the natural log of per capita spending on the natural log of local prices, calculated using both the MRI and the RPP. We obtain per capita state-level spending for fiscal year 2012 from Gordon, Auxier, and Iselin (2016). Both the MRI and RPP are calculated for calendar year 2012. In column (1), we use 0.618 + 0.382*MRI as the price index in order to make the results comparable, where 0.382 is the housing share of total expenditures in the Consumer Expenditure Survey (CE).

Online Appendix

For "The Geography of Disadvantage: Do Cost-of-Living Adjustments Improve Poverty Measurement and Program Targeting?"

by Bruce D. Meyer, Derek Wu, and Brian Curran*

* Any opinions and conclusions expressed herein are those of the author(s) and do not represent the views of the U.S. Census Bureau. All results were approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY20-ERD002-020 and CBDRB-FY2021-CES005-016.

A.1. Detailed Description of Data Sources

In this section, we describe the survey and administrative data used in this paper and the methods we use to link the data sources. We focus on reference year 2010, since this is a year for which we have a relatively complete set of administrative records covering all income sources.

Survey Data

Our survey data pertain to calendar year 2010 and come from the 2011 Current Population Survey Annual Social and Economic Supplement (CPS) and the 2008 Panel of the Survey of Income and Program Participation (SIPP). Both surveys are designed to be representative of the civilian non-institutional population of the United States. The 2011 CPS interviewed 75,000 households between February and April of 2011 about their incomes in calendar year 2010. The 2008 SIPP was a longitudinal survey that followed 42,000 households for up to 16 four-month waves, though not all households were observed for all 16 waves due to survey attrition.

For the CPS, we also bring in the publicly available SPM Research File produced by the Census Bureau. This dataset includes information necessary to calculate the SPM for all individuals in the CPS, including every individual's SPM reference unit structure, SPM income, SPM threshold, and geographic adjustment factor. Furthermore, we use the 5-year American Community Survey (ACS) to construct the Median Rent Index, which forms the geographic adjustment for the SPM and is therefore the primary index that we consider in this paper

While the default reference period for the CPS is a calendar year, the reference period in the SIPP is four consecutive months. We therefore combine information across multiple interview

waves in the SIPP to calculate annual incomes. This decision not only makes the CPS and SIPP income measures more comparable, but it also facilitates the use of calendar year tax data. As our first step, we take as our analysis sample all individuals who appear in reference month 4 of Wave 6 (which spans April-July 2010). Then, we incorporate information on survey incomes from other months in 2010 during which the individuals in the analysis sample appear. Lastly, we proportionately scale up survey incomes for the 21% of individuals who are interviewed for only a portion of the year. This method will overstate incomes for individuals who leave the survey because of death, institutionalization, or unemployment, but understate incomes for those who do not respond because of increased employment, for example.

In addition to collecting monthly data on a rich set of income sources, the SIPP collects measures of material well-being, certain expenses, and household structure in topical modules administered in the final month of various interview waves. The topical module corresponding to Wave 6 assesses adult well-being and allows us to analyze five broad domains of material well-being measures: material hardships, home quality problems, appliances owned, food security, and health. Because this topical module corresponds to reference month 4 of Wave 6, all members of our reference group appear in this module. As part of constructing the SPM using the SIPP, we must also incorporate certain expenses. The topical modules for Waves 4 and 7 cover many of these expenses, including medical and childcare expenses. However, due to survey attrition, 11% of individuals who appear in reference month 4 of Wave 6 do not appear in Wave 7's topical module, so we instead use Wave 4 information for these individuals. The topical modules for Waves 4 and 7 also contain information on assets owned, which constitute another measure of material well-being that we analyze. Lastly, the topical module for Wave 2 contains information on household structure necessary to construct SPM reference units.[28]

Administrative Data

We also bring in a number of administrative data sources. We first discuss the administrative records used to measure income. Earnings records come from Internal Revenue Service (IRS) W-2 Forms, the Detailed Earnings Record (DER) database of the Social Security Administration (SSA), and IRS 1040 Forms. IRS 1040 Forms also contain information on various

[28] This topical module allows us to find out which members of a household are cohabiting partners and which members are unrelated children. This information is then used to construct sharing units.

forms of asset income, including interest and dividends. The IRS 1040 extracts do not contain actual amounts corresponding to taxes paid and tax credits received, although they cover enough line items (e.g., Adjusted Gross Income (AGI), filing status, etc.) that we can simulate tax liabilities and credits relatively accurately. Data on retirement distributions come from IRS 1099-R Forms, which cover gross payments from employer-sponsored plans and Individual Retirement Account (IRA) withdrawals.

We also have a number of administrative program participation records from government agencies. Social Security benefit amounts come from the SSA's Payment History Update System (PHUS) file. Using the SSA's Master Beneficiary Record (MBR), we can distinguish between payments from Old-Age and Survivors Insurance (OASI) and payments from Social Security Disability Insurance (DI). Supplemental Security Income (SSI) benefits – covering both federal and federally-administered state payments – come from the SSA's Supplemental Security Record (SSR) file, and Service-Connected Disability payments to veterans come from the Department of Veterans Affairs. Finally, housing assistance records come from the Public and Indian Housing Information Center (PIC) and Tenant Rental Assistance Certification System (TRACS) files, which cover all public and subsidized housing programs under the jurisdiction of the Department of Housing and Urban Development (HUD) but miss payments associated with housing programs administered by the Department of Agriculture (USDA), states, and localities.[29] For this paper, we do not bring in administrative data from state agencies on SNAP or TANF, because these program data are only available for a subset of states and we want our analysis sample to cover every state in the nation.

We also use administrative records to construct additional measures of well-being. First, we use IRS tax records from tax years 2008, 2009, 2011, and 2012 to construct a measure of permanent income, which includes AGI from Forms 1040 for individuals who filed a tax return and wages and retirement distributions from W-2s and 1099-Rs, respectively, for individuals who did not file a tax return. Second, we use the Social Security Administration's Numident file to calculate mortality rates, relying on its information on dates of death for all individuals with Social Security Numbers in the United States.

[29] We calculate a household's benefit amount as the difference between the gross rent and actual tenant payment. For public housing units, we impute gross rent amounts based on the average rent by zip code and household size in a given year. Olsen (2003, 2019) finds that the gross rents used to calculate housing assistance amounts are close to market rents and thus similar to the valuation placed by private renters on the units.

A.2. Methods for Constructing Poverty Measures

Description of Official Poverty Measure (OPM)

To provide some context for the SPM and CIPM, we start by briefly describing its predecessor – the Official Poverty Measure (OPM). The OPM uses pre-tax money income as its resource measure, calculated for a sharing unit consisting of a family or single unrelated individual. Poverty thresholds are based on the cost of a food plan consisting of a nutritionally balanced, low-cost diet for families of different sizes and composition. Because the cost of the plan varies by family size and composition, it implicitly embeds an equivalence scale that accounts for different food needs across different types of families.

However, the OPM features several well-documented shortcomings. Its resource definition does not incorporate in-kind benefits and tax credits, nor does it subtract tax liabilities – as a result, it fails to reflect the full set of resources available to a family for consumption. In addition, the equivalence scale implicit in the OPM thresholds exhibits a number of anomalies, in some cases suggesting that children are more costly than adults and failing to exhibit monotonically decreasing marginal increments for additional individuals (Ruggles 1990). More generally, the OPM thresholds have been criticized for reflecting only economies of scale in food (and not other goods) and for being anchored to 1963 values that have since been updated only for price changes (which do not fully reflect standard-of-living changes in the U.S.). Finally, the OPM does not classify a cohabiting unmarried couple as a single sharing unit, even though such a couple may pool resources in similar ways as a married couple that the OPM does classify as a single sharing unit. For a fuller discussion of these and other issues, see National Research Council (1995) and Blank (2008).

Constructing the Supplemental Poverty Measure (SPM)

Resource Measure

Unlike the Official Poverty Measure (OPM), which uses pre-tax money income as its definition of income or resources, the SPM uses as its resource measure pre-tax money income plus non-cash transfers net of certain expenses and taxes. Specifically, the SPM resource measure adds to pre-tax money income the estimated value of benefits received through SNAP, housing assistance, school meals, the Special Supplemental Nutrition Program for Women, Infants, and

Children (WIC), and the Low Income Home Energy Assistance Program (LIHEAP). It then subtracts federal and state income tax liabilities net of credits and payroll taxes. Finally, it subtracts expenses (or their estimates) for work, childcare, child support, and health care.

In the CPS, we utilize SPM incomes calculated by the Census Bureau and available in the SPM Research File. Note that the SPM incomes in this file rely on the public-use CPS with top-coded variables, while the estimates in the official SPM report rely on the internal version of the CPS with no top-coding (Fox 2019).[30] Nevertheless, we continue to use the variables on the public-use Census Bureau file because the vast majority of individuals have no top-coded incomes, and imputing variables would lead to additional non-comparabilities between our estimates and internal Census ones. Most of the SPM income components are based on amounts explicitly asked about in the CPS, while some have amounts imputed either from survey reports of receipt (for school lunch, housing assistance, and WIC) or from related variables (for work expenses and Medicare Part B premiums). Lastly, tax liabilities and credits in the CPS are imputed using the CPS tax calculator. For a detailed summary of how the components of SPM income are constructed in the CPS, see Fox (2019).

In the SIPP, we directly calculate the components of SPM income other than pre-tax money income, with our work being heavily influenced by Short (2014). For in-kind benefits, we use reported survey amounts for SNAP and LIHEAP (at the family and household level, respectively) and impute amounts for housing assistance, school meals, and WIC for those reporting program receipt.[31] We calculate the value of housing assistance by subtracting monthly rent paid (reported in the SIPP) from imputed fair market rent.[32] We impute fair market rent by matching to HUD fair market rent data based on county, year, and the number of bedrooms.[33] To calculate the annual

[30] Therefore, an individual's poverty status when estimated using the public-use file may be different than his/her poverty status estimated using the internal file. Using the public SPM research file for 2010, there were an estimated 48,934,000 people in SPM poverty. However, on the official SPM report there were an estimated 49,094,000 people in SPM poverty.

[31] For LIHEAP, note that the SIPP's estimates do not include subsidies paid directly to utility companies while the CPS asks about those subsidies.

[32] Another difference between the SIPP and CPS is that amounts for rent paid are reported in the SIPP, while they must be imputed in the CPS.

[33] The number of bedrooms is not reported in the SIPP, so we must impute it. We construct the number of bedrooms in the survey via the following algorithm: (1) for childless households, give 1 bedroom to households with 1 or 2 adults and add 1 bedroom for each additional adult, (2) for households with children, give 2 bedrooms to households with 1 or 2 same-gender children and add 1 bedroom for each additional child. This attempts to follow HUD's minimal requirements that a dwelling must have at least one bedroom for every 2 people and that people of opposite gender (except for couples and very young children) should not be required to occupy the same bedroom (Currie and Yelowitz 2000).

value of free/reduced price school lunch, we multiply the number of children receiving free lunch (which is reported in the SIPP) by the daily federal reimbursement rate for free lunch ($2.68) and the average number of school days per year (179).[34] We then perform parallel calculations for reduced-price lunch, free breakfast, and reduced-price breakfast.[35] For WIC, we value the subsidy for every person reporting receipt using USDA's estimates of average WIC food costs per person.[36]

Next, we calculate work-related expenses in the SIPP by multiplying 85 percent of the median weekly work expenses for adult workers by the number of weeks worked per month.[37] Childcare expenses, which are asked about in the topical modules for Waves 4 and 7, are calculated as the sum over all children of the weekly amount paid on childcare multiplied by the number of weeks worked by the parent. Child support paid and medical out-of-pocket expenditures (MOOP) are reported at the person level in the topical modules for Waves 4 and 7. We also subtract Medicare Part B premiums, which we calculate from survey-reported marital status and survey-reported total income.[38] To complete the SPM resource measure, we calculate tax liabilities and credits. While the SIPP contains a topical module on taxes paid, it contains sparse and incomplete data so we calculate tax liabilities and credits on our own. We start by generating tax units based on reported family structure in the SIPP, and then – using reported incomes and demographic characteristics – we simulate taxes using the TAXSIM calculator from the National Bureau of Economic Research (NBER).[39] Using this method, we are able to calculate federal and state income and payroll tax liabilities, as well as tax credits including the Earned Income Tax Credit (EITC), Child Tax Credit (CTC), Child and Dependent Care Credit, and Making Work Pay Credit. For a more detailed discussion of how these taxes are calculated, see Meyer et al. (2020).

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[34] Reimbursement rates are published in the Federal Register: https://www.govinfo.gov/content/pkg/FR-2009-07-15/pdf/E9-16745.pdf.

[35] The daily reimbursement rate is $2.28 for reduced-price lunch, $1.46 for free breakfast, and $1.16 for reduced-price breakfast. To calculate the annual value of these programs, we multiply the daily reimbursement rate by 179 school days per year. Another difference between the CPS and SIPP is that the SIPP asks about receipt of both free/reduced lunch and breakfast, while the CPS asks only about receipt of free/reduced lunch. As a result, a value of zero is always assigned for school breakfast in the CPS.

[36] In 2010, the USDA estimated an average monthly food cost of $41.43 per person.
See https://fns-prod.azureedge.net/sites/default/files/resource-files/wisummary-7.pdf.

[37] This follows the methodology used in the official SPM report (Fox 2019).

[38] The table of premium amounts can be found at https://www.cms.gov/newsroom/fact-sheets/cms-announces-medicare-premiums-deductibles-2010.

[39] We assume all married couples file jointly. Dependents are children under the age of 19, children under the age of 24 and enrolled in school, individuals that are permanently and totally disabled, or other relatives with income below $3,650. We calculate taxes at the family level, and then aggregate family-level amounts to the sharing unit level if there are multiple families per sharing unit.

Resource Unit

While the OPM uses a family (defined as all people living together related by birth, marriage, or adoption) as its resource unit, the SPM resource unit additionally includes cohabiting partners, unrelated children under the age of 15, and foster children between the ages of 15 and 22. In the CPS, we use resource unit identifiers present in the SPM Research File. In the SIPP, we rely on the topical module for Wave 2 – which contains detailed household relationship information specifically identifying cohabiting partners and unrelated and foster children – to construct the SPM resource unit. Because this household relationship information is only asked about during Wave 2, we cannot use it to identify relationships for individuals entering the survey after Wave 2. For the 12% of individuals who are in our reference group but do not appear in Wave 2, we check whether they enter an existing family. Approximately half of these individuals enter into existing families, and we assign them to their respective families' SPM resource units. For the other half of these individuals who do not enter into existing families, we assign them their own SPM resource unit.

Poverty Thresholds and the Equivalence Scale

The SPM uses different poverty thresholds than the OPM does and adjusts the thresholds in a different way. The SPM thresholds are based on out-of-pocket spending on food, shelter, clothing, and utilities. The threshold is calculated as 1.2 times the average spending of those in the 30^{th}-36^{th} percentiles of spending on these expenses, computed using five years of Consumer Expenditure Survey (CE) data. However, the SPM differentiates between three housing tenure groups (homeowners with mortgages, homeowners without mortgages, and renters) and calculates spending separately for these groups (implicitly assuming they are otherwise the same).

The SPM then applies two different adjustments to this base threshold. The first is an equivalence scale that adjusts the threshold based on the size of the reference unit. In particular, we multiply the base threshold by a three-parameter SPM equivalence scale, calculated using the demographic characteristics of the resource unit and divided by the scale for a two-adult, two-child family. The second adjustment is a geographic adjustment, which uses data from the 5-year ACS files to adjust base thresholds for differences in median gross rents (for two-bedroom apartments) across geographic areas. These medians are divided by the national median for the same unit type

to calculate the MRI, and are computed for each of the 264 metropolitan statistical areas (MSAs) that can be publicly identified in the CPS ASEC. For areas that do not fall into any of the publicly identified MSAs, medians are estimated for all non-metro areas in a state as well as for a combination of all other metro areas within a state. This gives 358 adjustment factors for the year 2010: 264 from MSAs, 48 from states' non-metro areas, and 46 from states' all other metro areas.[40]

Putting these all together, the final SPM threshold is found by multiplying the base threshold together with the equivalence scale factor for family structure and the geographic adjustment factor (which scales the MRI by the share of expenditures taken up by housing costs). More formally, the threshold for an SPM unit is given by:

$$SPM\ Threshold_{t,ac,sm} = (Base\ Threshold)_t \times \frac{(Equivalence\ Scale\ Factor)_{ac}}{E} \times [(Housing\ Share_t \times MRI_{sm}) + (1 - Housing\ Share_t)], \quad (1)$$

where t is the unit's housing tenure, a and c represent the number of adults and children in the unit (respectively), and s and m denote the unit's state and MSA (respectively). The constant E is the equivalence scale for a two-adult, two-child family. The components of Equation (1) that vary by housing tenure and resource unit composition can be further broken down as follows:

$$Base\ Threshold_t = \begin{cases} \$25{,}018 & \text{for } t = \text{Owner with Mortgage} \\ \$20{,}590 & \text{for } t = \text{Owner without Mortgage} \\ \$24{,}391 & \text{for } t = \text{Renter} \end{cases}$$

$$Equivalence\ Scale\ Factor_{ac} = \begin{cases} (adults)^{0.5} & \text{for } a \geq 1,\ c = 0 \\ (adults + 0.8 \times first\ child + 0.5 \times other\ children)^{0.7} & \text{for } a = 1,\ c \geq 1 \\ (adults + 0.5 \times children)^{0.7} & \text{otherwise} \end{cases}$$

$$Housing\ Share_t = \begin{cases} 0.510 & \text{for } t = \text{Owner with Mortgage} \\ 0.404 & \text{for } t = \text{Owner without Mortgage} \\ 0.497 & \text{for } t = \text{Renter} \end{cases}$$

[40] We extract these 358 adjustment factors from the Census Bureau's SPM file for the CPS and merge them onto the SIPP, assigning the correct adjustment factor based on MSA, state, and metro status. Not all states have non-metro areas or other metro areas, leading to less than 50 such adjustment factors for non-metro areas and for other metro areas.

The values for the base threshold by housing tenure, all for a unit with two children and two adults, correspond to 2010.[41]

Constructing the Comprehensive Income Poverty Measure (CIPM)

Resource Measure

For the second poverty measure that we analyze (the CIPM), we use the CID to construct an alternative resource measure that differs from the SPM resource measure conceptually and brings in administrative data to measure incomes more accurately. We begin by discussing the conceptual differences. First, in line with the OPM and in contrast with the SPM, the CIPM resource measure does not subtract expenses for work, childcare, child support, and health care. While subtracting these expenses may theoretically yield a resource measure that better approximates the resources available for consumption, prior research has also shown that subtracting certain expenses (e.g., medical costs) identifies a poor population that appears less materially deprived (Meyer and Sullivan 2012). Second, the CIPM resource measure estimates a flow value of services from home and car ownership as well as an annuity value of other net assets. Specifically, we estimate the rental equivalent of home ownership by multiplying home values by 8% and the service flow from vehicle ownership by multiplying vehicle values by 13%.[42] For other assets (namely business, liquid, financial, and pension assets) net of housing, vehicle, and other debt, we follow Wolff et al. (2012) in calculating an annuity value using separate rates of returns for each type of asset grouping. Because the CPS does not ask about assets in detail, we are only able to estimate these asset flows in the SIPP (using information from the topical modules for Waves 4 and 7).

Next, we discuss the measurement differences. First, we bring in multiple administrative sources to construct improved measures of earnings. Specifically, we take the higher of wages in the DER, W-2s, and 1040s added to self-employment earnings from the DER to obtain a combined

[41] See https://www.census.gov/prod/2011pubs/p60-241.pdf for the base thresholds by housing tenure. See https://www.bls.gov/pir/spm/spm_threshold_200518.xlsx for the housing shares by housing tenure.

[42] The 8% of home value is close to the mean ratio of the rental equivalent to home value from the Consumer Expenditure (CE) Interview Survey. The 13% of vehicle equity is the sum of the annual depreciation rate (which is calculated from the CE Interview Survey using the sale prices of new and used vehicles over time and estimated to be 13%) and the interest rate on certificates of deposit (estimated to be close to zero in 2010 for 1- and 2-year interest rates).

measure of total administrative earnings. However, we continue to use survey earnings that exceed combined administrative earnings if they reflect earnings that are plausibly missed in the tax records.[43] Next, we replace survey reports of asset income (namely interest and dividends), retirement income, Social Security, SSI, and veterans' benefits with their counterparts from the administrative data. We then use TAXSIM to calculate tax liabilities and credits, relying on tax unit structure and incomes from the IRS tax records as inputs. We also calculate taxes for units who do not link to a 1040 (in the event that they are late filers or had taxes withheld), relying on their survey-reported incomes and family structure. Finally, we replace survey values of housing assistance with administrative values, although we treat survey respondents reporting receipt that do not appear in the administrative data as true recipients (since the administrative data cover only HUD-administered programs).

Resource Unit

The CIPM uses the same resource unit as the SPM – namely a family and additional cohabiting partners, unrelated children under the age of 15, and foster children between the ages of 15 and 22.

Poverty Threshold and Equivalence Scale

The CIPM also uses nearly the same poverty thresholds as the SPM, with the key exception being that the base threshold and housing share (in the geographic adjustment factor) in the CIPM no longer vary by housing tenure. Because the CIPM resource measure explicitly accounts for the flow value of home ownership, there is no longer a reason to set distinct thresholds (implicitly accounting for differences in available resources) for distinct housing status groups. The three-parameter equivalence scale used in the CIPM thresholds remains the same as that used in the SPM thresholds. More formally, the threshold for a CIPM unit is given by:

[43] We incorporate survey earnings only when they are not imputed, when other employment characteristics (hours worked, weeks worked, industry of job, job occupation, and size of employer) are not imputed, and when one of the following conditions holds: 1) earnings are missing across all administrative sources, 2) the number of survey-reported employers exceeds the number of employers in the administrative data, 3) the respondent reports being self-employed in the survey, or 4) the respondent reports working for a small employer in the survey. In the CPS, we continue to use survey earnings for only 27% of all individuals whose survey earnings exceed their administrative earnings.

$$CIPM\ Threshold_{ac,sm} = Base\ Threshold \times \frac{(Equivalence\ Scale\ Factor)_{ac}}{E} \times [(Hous.\ Share \times MRI_{sm}) + (1 - Hous.\ Share)], \quad (2)$$

where a and c represent the number of adults and children in the unit (respectively) and s and m denote the unit's state and MSA (respectively). The constant E continues to designate the equivalence scale for a two-adult, two-child family. We set the base threshold in Equation (2) equal to $22,113 (the official poverty threshold for a two-adult, two-child family) and the housing share equal to 0.382 (which is the share of overall consumption dedicated to housing in 2010).

A.3. Detailed Description of Geographic Price Indices

A number of different price indices have been proposed to adjust poverty thresholds by geography. The Supplemental Poverty Measure (SPM) relies on the Median Rent Index (MRI) to geographically adjust its thresholds (Fox 2019). Using information from the 5-year American Community Survey (ACS) files, the MRI is calculated as the ratio of the median gross rent for a two-bedroom unit with a complete kitchen and bathroom in a specific metropolitan area or state to the median gross rent for the same type of unit in the U.S. The MRI is calculated for all Metropolitan Statistical Areas (MSAs) with populations of at least 100,000. Within each state, all metropolitan areas that have fewer than 100,000 people are grouped together into an "other metropolitan" category and all non-metropolitan areas are grouped together in a "non-metropolitan" category. In the SPM, one multiplies the share of the SPM poverty threshold that is attributable to housing and utility expenditures by the MRI to calculate the MRI-adjusted SPM poverty threshold.

Closely related to the MRI is a rescaled version of the MRI proposed by Renwick (2018, 2019) that seeks to reflect amenities in geographic adjustments of poverty rates. Renwick argues that the MRI will over-adjust thresholds if places with higher median rents also have greater amenities and will under-adjust thresholds if places with higher average rents have lower average amenities. In order to adjust for amenities, Renwick (2018) cuts the variation in the MRI index in half. This rescaled index is admittedly an "arbitrary" adjustment because the literature has established no clear methodology for incorporating amenities (p. 5).

Another proposed method for adding geographic adjustments to poverty is to use Regional Price Parities or RPPs (Aten 2005, Aten and D'Souza 2008). Calculated by the Bureau of Economic Analysis (BEA), RPPs are spatial price indices that measure price differences in a broad set of goods across regions. They are constructed in two stages. First, price data and expenditure weights are derived from the Consumer Price Index (CPI) and the Consumer Expenditure (CE) survey.[44] These data come from over 200 individual items and comprise eight broad categories: housing, transportation, food, education, recreation, medical, apparel, and other. Thus, RPPs rely on a wider set of goods and services than the MRI, which only accounts for differences in rents. In all, this first stage yields information for 38 urban areas plus four rural regions. Second, these price levels and weights from these urban and rural regions are applied to all counties in the US. This stage incorporates data for housing from the ACS: rent levels are estimated annually for each state and across 3 years for metropolitan areas. These rent levels are quality-adjusted using a hedonic model that controls for characteristics such as type of structure, number of bedrooms, number of rooms, when it was built, and whether or not utilities are included in rent. One then multiplies the entire poverty threshold by the RPPs, as RPPs are designed to measure broad price levels (Bureau of Economic Analysis 2016).

A final method for incorporating geographic adjustments to poverty is to use food, apparel, and rent regional price parities or FAR RPPs (Renwick et al. 2014, Renwick, Figueroa, and Aten 2017). While RPPs cover many goods and services, many of these items are not included in the SPM thresholds. In contrast, FAR RPPs cover only the subset of goods in the RPPs that are also included in the SPM poverty threshold – namely food, apparel, and rent. In the case of the SPM, one multiplies the share of the SPM poverty threshold attributable to food, apparel, and rent expenditures by the FAR RPP to calculate the FAR-RPP-adjusted SPM poverty thresholds.

Renwick et al. (2014) and Renwick, Figueroa, and Aten (2017) empirically compare the MRI, RPP, and FAR RPP by computing SPM poverty using each of these three measures. The authors compute various SPM poverty measures for reference years 2011 and 2015 and find significant differences between the measures.[45] The authors suggest that the differences between

[44] Specifically, expenditure weights are found using CPI expenditure weights, BEA's personal consumption expenditures, and ACS rent expenditures.

[45] For 2011, they find that the national poverty rate was 16.1% using the MRI, 15.6% using the RPP, and 16.4% using the FAR RPP. For 2015, the national poverty rate was 14.3% using the MRI, 13.8% using the RPP, and 13.7% using the FAR RPP. They also find that for 2009-2011, 19 states and Washington, D.C. had FAR RPP poverty rates higher

the indices are driven by the different weights given to housing expenditures. In the MRI, housing expenditures represent between 40 and 51 percent of the threshold while in the FAR RPP, housing expenditures represent between 28 and 65 percent of the threshold.[46] Dubay, Wheaton, and Zedlewski (2013) also assess how adjustments to poverty guidelines using the MRI and RPP would affect eligibility for several government transfer programs. The authors find that SNAP eligibility would decrease slightly under both indices, while Medicaid eligibility would increase under the MRI and decrease under the RPP.[47]

A.4. Measures of Well-Being from Survey and Admin. Data

2011 CPS ASEC

- Education attained [A_HGA]
- Health status [HEA]

SIPP 2008 Panel - Adult Well-Being (Wave 6 Topical Module, May 2010 – Aug. 2010)

Appliances

- Household has air conditioner [EADAIR]
- Household has cell or mobile phone [EADCELL]
- Household has clothes dryer [RADDRYR]
- Household has color television [EADTELV]
- Household has dishwasher [EADDISH]
- Household has microwave [EADMICR]
- Household has personal computer [EADCOMP]
- Household has washing machine [RADWASH]

Education

- Highest grade achieved [EEDUCATE]

Food Security

- Ate less than felt you should [EAFLESS]
- Children were not eating enough [EAFCHLD]

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than MRI poverty rates, 22 states had MRI poverty rates higher than FAR RPP poverty rates, and 9 states had a statistically insignificant difference. Lastly, they find that for 2014-2015, 5 states and Washington, D.C. had FAR RPP poverty rates higher than MRI poverty rates, 34 states had MRI poverty rates higher than FAR RPP poverty rates, and 11 states had a statistically insignificant difference.

[46] Variation in housing expenditure shares leads to a range of thresholds (rather than a single value) for both indices because the MRI's housing shares vary by housing tenure: the housing share for owners without a mortgage is 40 percent, while the housing share for owners with a mortgage and renters is about 50 percent. On the other hand, the FAR RPP's housing shares vary by metro area. The housing shares range from 28 percent in non-metropolitan West Virginia to 65 percent in other metropolitan Florida.

[47] While the authors find small effects at the national level, there are larger differences across states. In general, eligibility for government transfers increases in more urban states and decreases in more rural states.

- Couldn't afford balanced meals [EAFBALN]
- Cut size or skipped meals [EAFSKIP]
- Didn't eat for a whole day [EAFDAY]
- Food we bought just didn't last [EAFLAST]
- Not enough to eat – 2 months ago [EAFDM3]
- Not enough to eat – 3 months ago [EAFDM2]
- Not enough to eat – 4 months ago [EAFDM1]
- Not enough to eat – current month [EAFDM5]
- Not enough to eat – last month [EAFDM4]
- Sufficiency of food eaten in household [EAFOOD1]

Health

- General quality of health [EHSTAT]
- Physical, mental, or other health condition that limits the kind or amount of work that can be done [EDISABL – Wave 6 Core File]
- Health or condition prevents work at a job or business [EDISPREV – Wave 6 Core File]

Home Quality

- Problem with broken windows [EAHWIND]
- Problem with exposed electrical wires [EAHWIRE]
- Problem with holes in the floor [EAHHOLE]
- Problem with holes or cracks in wall or ceiling [EAHCRAC]
- Problem with leaking roof [EAHLEAK]
- Problem with pests [EAHPEST]
- Problem with plumbing that doesn't work [EAHPLUM]

Material Hardships

- Ability to meet essential expenses (defined as mortgage or rent payments, utility bills, or important medical care) [EABMEET]
- Did not pay gas, oil, or electricity bills [EABGAS]
- Did not pay rent or mortgage [EABRENT]
- Did not see a dentist when needed [EABDENT]
- Did not see a doctor when needed [EABDOCT]
- Evicted from home or apartment [EABEVCT]
- Gas or electric company turned off service [EABCUT]
- Telephone company disconnected service [EAPBHON]

Public Services and Safety

- Adequacy of public transportation [EAPTRAN]
- Afraid to walk alone at night [EACWALK]
- Carry something with you when go out [EACARRY]
- Public services undesirable, would like to move [RAPMOVE]
- Satisfaction with fire department services [EAPFIRE]
- Satisfaction with hospitals, health clinics, doctors [EAPHOSP]

- Satisfaction with police services [EAPOLIC]
- Satisfaction with public schools [EAPSCHL]
- Satisfaction with public services [EAPSAT]
- Stayed at home at certain times [EACSTAY]
- Take someone with you when go out [EACWITH]
- Threat of crime enough that would move [RACMOVE]

SIPP 2008 Panel – Assets and Liabilities (Wave 7 Topical Module, Sep. 2010 – Dec. 2010)

- Net worth [THHTNW]
- Total Liquid Assets [Multiple variables]
- Home equity [THHTHEQ]
- Vehicle equity [THHVEHCL]
- Other assets [Multiple variables]

Administrative Data

- Permanent income from tax records. We use 2008, 2009, 2011, and 2012 tax income
    - We define tax income as adjusted gross income from the 1040 if the individual filed a 1040. If the individual didn't file a 1040, we use as tax income the sum of income reported on forms W-2 and 1099-R
- Mortality from the Numident. We have mortality records from the Numident up until March of 2019

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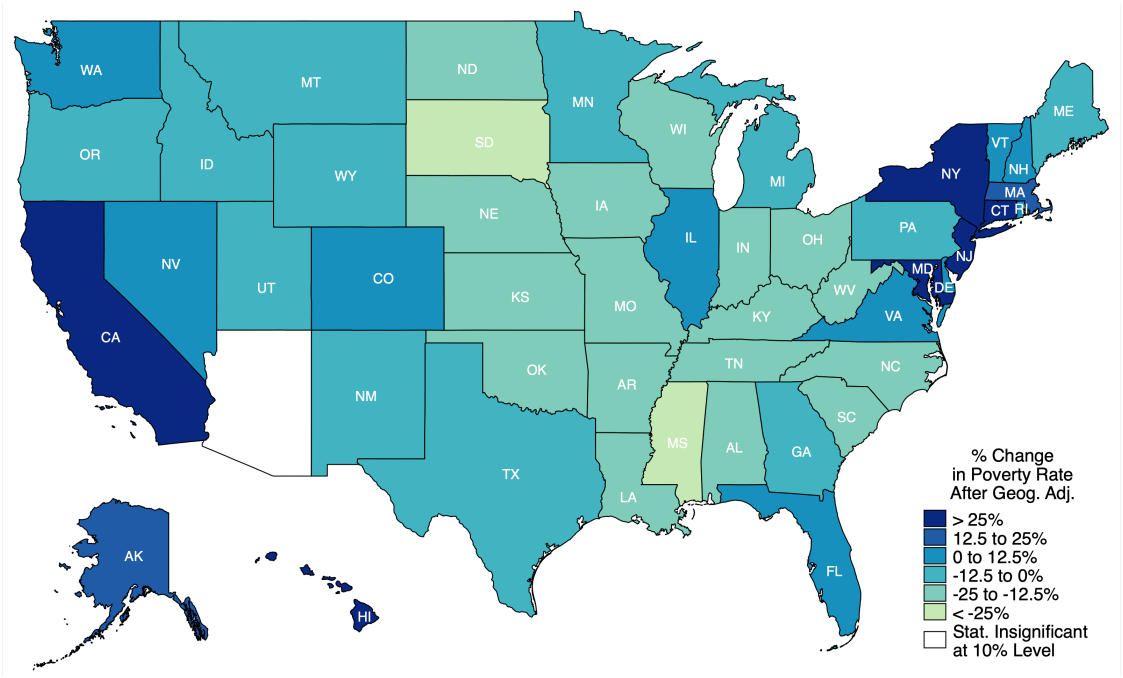
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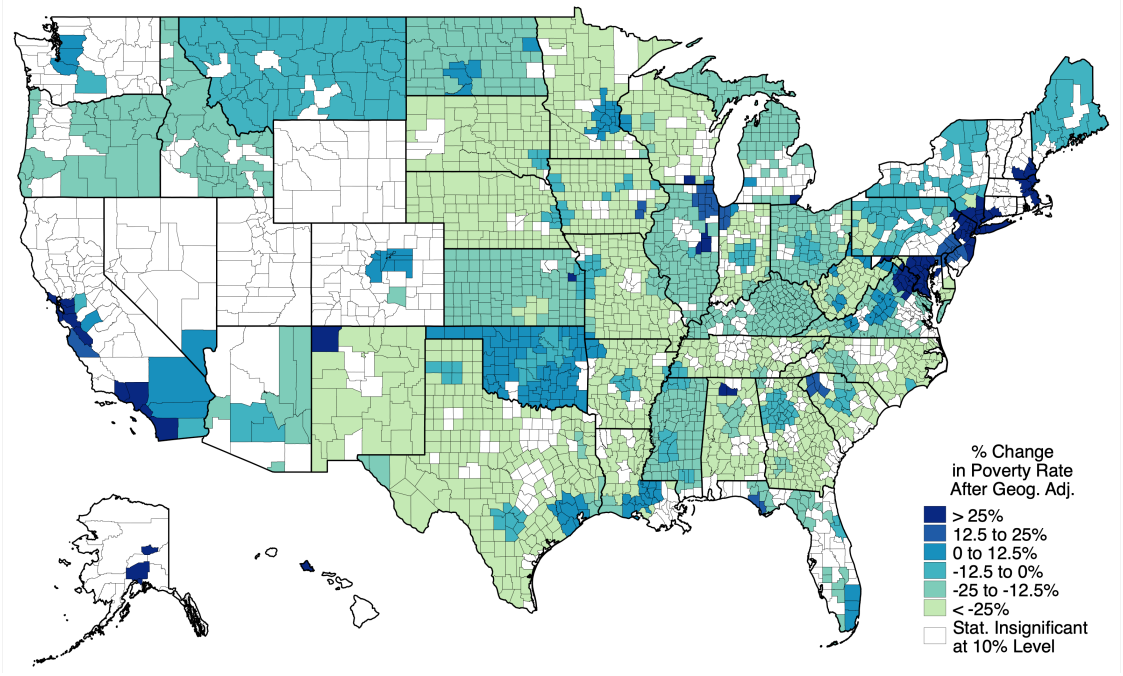
B. Appendix Figures and Tables

Figure A1. Map of Percent Changes in Poverty Rates After Geographic Adjustments (Using RPPs)

(a) By State



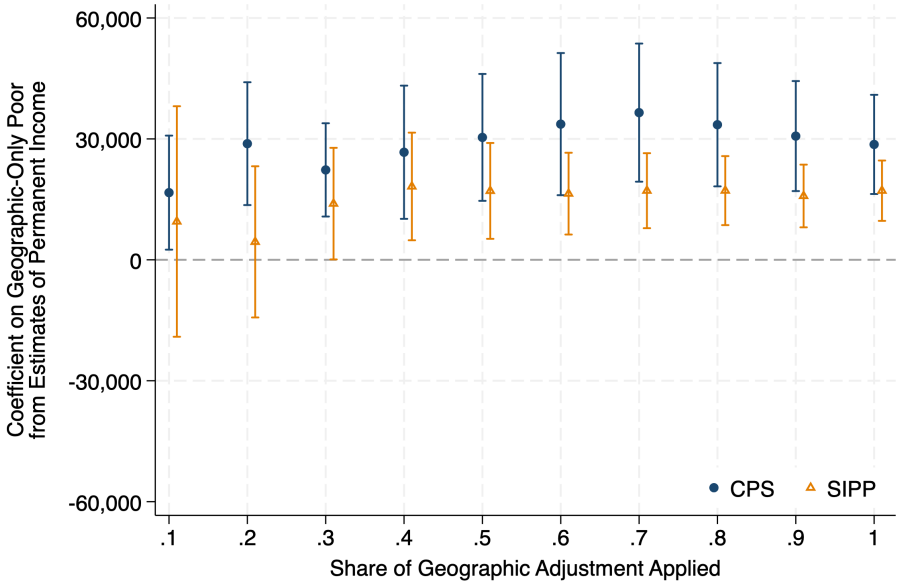
(b) By CBSA



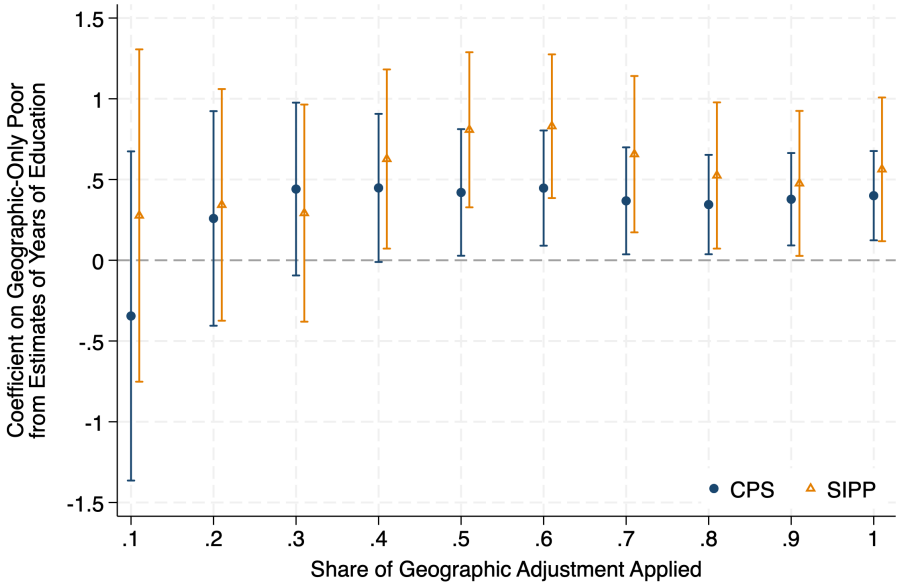
Data: 2010-2012 CPS ASEC (public-use)
Notes: These maps show the differences in poverty rates by state and CBSA before and after geographic adjustments (where the national poverty rates are anchored to 15.1%), using Regional Price Parities (RPPs) rather than the Median Rent Index (MRI). See notes to Figure 2 for more detail.

Figure A2. Effects of Partial Geographic Adjustments on Characteristics of the Poor (SPM)

(a) Permanent Income



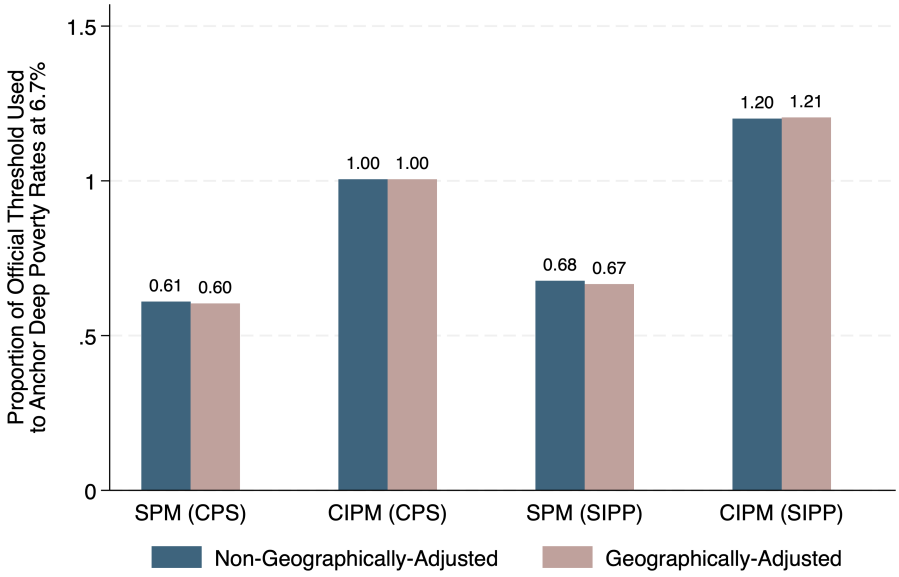
(b) Years of Education



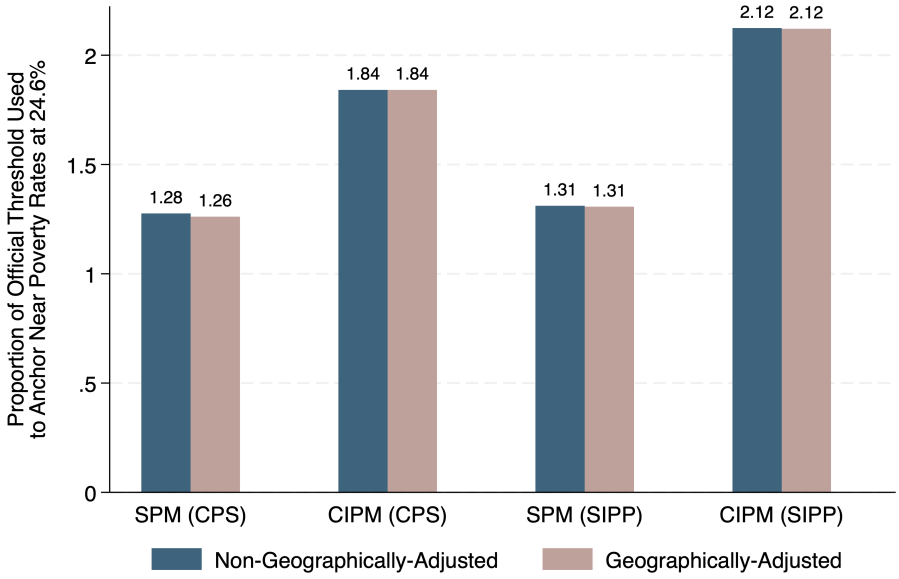
Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: These figures report coefficients on an indicator for being geographic-only SPM poor (vs. non-geographic-only SPM poor) from regressions of permanent income and years of education on geographic poverty categories and covariates. Across estimates, the geographic adjustment factor is scaled from 0.1 to 1.0, where 1.0 corresponds to the full geographic adjustment. The sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS). Confidence bands are at the 95% level.

Figure A3. Scaling Factors Used to Anchor Deep and Near Poverty Rates at Official Levels

(a) Deep Poverty

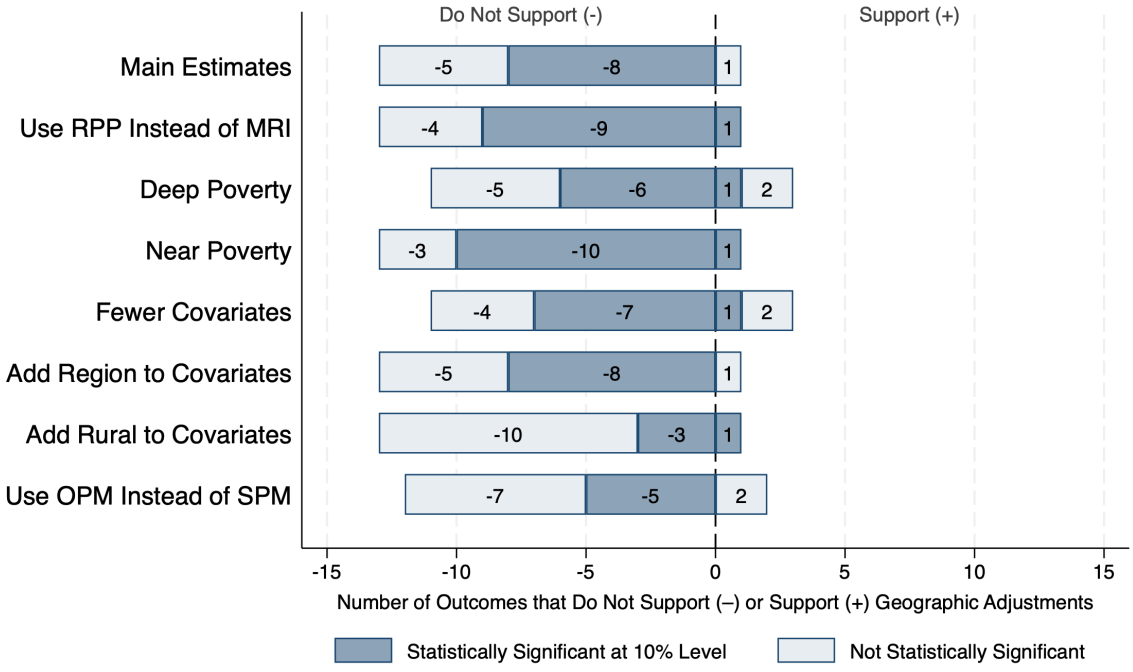


(b) Near Poverty



Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This figure shows the fixed factors by which the SPM and CIPM thresholds are scaled in both the CPS and SIPP so that deep and near poverty rates are anchored at 6.7% and 24.6%, which correspond to the rates in 2010 using survey-reported pre-tax money income and official thresholds.

Figure A4. Number of Summary Outcomes Supporting or Not Supporting Geographic Adjustments Across Specifications (Survey-Only Specifications)



Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This figure shows the number of summary outcomes (out of 14) for which a geographic adjustment identifies a more deprived population, using the SPM and across various survey-only specifications (the last one uses the OPM rather than SPM). Outcome domains include mortality, permanent income, education, and health problems (in CPS and SIPP), and appliances, assets, food security problems, home quality problems, material hardships, and public services problems (in SIPP only).

Table A1. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (SPM)

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
Permanent Income (CPS & SIPP)					
CPS	**28,630*** **	**(6,278)**	**26,980**	**98,620**	**–**
SIPP	**17,150*** **	**(3,819)**	**33,870**	**92,930**	**–**
Years of Education (CPS & SIPP)					
CPS	**0.4000*** **	**(0.1410)**	**11.840**	**13.640**	**–**
SIPP	**0.5630*** **	**(0.2270)**	**12.060**	**13.700**	**–**
Mortality (CPS & SIPP)					
Died by 2015 (ind.) – *CPS*	-0.0038	(0.0071)	0.051	0.036	–
Died by 2019 (ind.) – *CPS*	-0.0149*	(0.0090)	0.098	0.064	–
Died by 2015 (head) – *CPS*	-0.0079	(0.0120)	0.071	0.040	–
Died by 2019 (head) – *CPS*	**-0.0226**	**(0.0140)**	**0.124**	**0.071**	**–**
Died by 2015 (ind.) – *SIPP*	-0.0047	(0.0073)	0.054	0.041	–
Died by 2019 (ind.) – *SIPP*	-0.0132	(0.0087)	0.089	0.069	–
Died by 2015 (head) – *SIPP*	-0.0068	(0.0130)	0.064	0.047	–
Died by 2019 (head) – *SIPP*	**-0.0259**	**(0.0165)**	**0.110**	**0.080**	**–**
Health Problems (CPS & SIPP)					
Poor/Fair Health Quality (ind.) – *CPS*	**-0.0603*** **	**(0.0137)**	**0.226**	**0.118**	**–**
Poor/Fair Health Quality (head) – *CPS*	-0.0597***	(0.0219)	0.344	0.166	–
Poor/Fair Health Quality (ind.) – *SIPP*	**-0.0711*** **	**(0.0148)**	**0.182**	**0.103**	**–**
Poor/Fair Health Quality (head) – *SIPP*	-0.1430***	(0.0333)	0.304	0.136	–
Health Condition Limits Work – *SIPP*	-0.0889***	(0.0133)	0.165	0.089	–
Health Condition Prevents Work – *SIPP*	-0.0675***	(0.0105)	0.114	0.056	–
Material Hardships (SIPP)					
Total Number	**-0.1550**	**(0.1370)**	**1.164**	**0.646**	**–**
Did Not Meet All Essential Expenses	-0.0386	(0.0377)	0.317	0.180	–
Did Not Pay Full Rent	-0.0208	(0.0257)	0.172	0.092	–
Evicted Because of Rent	0.0015	(0.0076)	0.007	0.005	+
Did Not Pay Full Energy Bill	-0.0338	(0.0326)	0.215	0.120	–
Had Energy Cut Off	-0.0060	(0.0130)	0.038	0.020	–
Had Telephone Service Cut Off	-0.0019	(0.0229)	0.084	0.043	–
Needed to See Doctor but Could Not	-0.0351	(0.0270)	0.162	0.084	–
Needed to See Dentist but Could Not	-0.0314	(0.0259)	0.168	0.102	–
Home Quality Problems (SIPP)					
Total Number	**-0.1230***	**(0.0654)**	**0.370**	**0.224**	**–**
Pests	-0.0206	(0.0250)	0.112	0.080	–
Leaking Roof	-0.0391*	(0.0205)	0.091	0.050	–
Broken Windows	-0.0556***	(0.0165)	0.082	0.031	–
Electrical Problems	0.0010	(0.0067)	0.012	0.007	+
Plumbing Problems	0.0004	(0.0109)	0.022	0.020	+
Holes or Cracks in Wall	0.0014	(0.0163)	0.037	0.029	+
Holes in Floor	-0.0113*	(0.0066)	0.014	0.007	–

Table A1. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (SPM) – cont.

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
Appliances (SIPP)					
Total Number	**-0.1900**	**(0.1660)**	**6.207**	**6.988**	**+**
Microwave	-0.0070	(0.0210)	0.942	0.975	+
Dishwasher	0.0584	(0.0371)	0.476	0.711	–
Air Conditioning	-0.1750***	(0.0327)	0.891	0.886	+
Television	0.0023	(0.0173)	0.961	0.985	–
Personal Computer	0.1440***	(0.0404)	0.550	0.793	–
Washing Machine	-0.1560***	(0.0317)	0.845	0.879	+
Dryer	-0.1160***	(0.0390)	0.784	0.858	+
Cell Phone	0.1110***	(0.0313)	0.758	0.900	–
Assets (SIPP)					
Total Wealth	**96,560****	**(44,810)**	**82,930**	**384,900**	**–**
Total Debt	36,980***	(10,130)	40,590	112,700	+
Net Worth	59,580	(45,130)	42,350	272,200	–
Home Equity	31,920***	(11,880)	40,200	114,400	–
Vehicle Equity	1,279***	(483)	3,743	7,324	–
Other Assets	63,370	(43,160)	38,990	263,200	–
Food Security Problems (SIPP)					
Total Number	**-0.1750**	**(0.1220)**	**1.022**	**0.460**	**–**
Not Enough Food	-0.0383**	(0.0161)	0.080	0.026	–
Food Bought Did Not Last	-0.0430	(0.0329)	0.289	0.147	–
Could Not Afford Balanced Meals	-0.0524*	(0.0288)	0.253	0.130	–
Children Not Eating Enough	0.0118	(0.0223)	0.069	0.032	+
Cut Size or Skipped Meals	-0.0330	(0.0242)	0.136	0.053	–
Ate Less Than Felt One Should	-0.0344	(0.0250)	0.144	0.058	–
Did Not Eat for Whole Day	-0.0044	(0.0138)	0.051	0.015	–
Public Services and Safety (SIPP)					
Total Num. of Public Service Problems	**-0.0298**	**(0.1300)**	**1.165**	**0.949**	**–**
Inadequate Public Transportation	-0.1220***	(0.0384)	0.263	0.206	–
Afraid to Walk Alone at Night	0.0286	(0.0274)	0.216	0.201	+
Carry Anything When Going Out	-0.0049	(0.0136)	0.054	0.060	–
Public Services Undesirable	0.0086	(0.0133)	0.024	0.019	+
Unsatisfied with Fire Department	-0.0021	(0.0134)	0.024	0.014	–
Unsatisfied with Hospitals	-0.0150	(0.0171)	0.091	0.064	–
Unsatisfied with Police	-0.0419**	(0.0206)	0.104	0.051	–
Unsatisfied with Public Schools	0.0159	(0.0191)	0.052	0.050	+
Unsatisfied with Public Services	-0.0191	(0.0166)	0.059	0.047	–
Stayed at Home for Safety Reasons	0.0571**	(0.0237)	0.118	0.102	+
Take Someone with You for Safety	0.0657***	(0.0215)	0.092	0.089	+
Threat of Crime Enough that Would Move	-0.0001	(0.0141)	0.069	0.045	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel

Notes: This table reports coefficient on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic SPM poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. Summary measures for each domain are bolded. The sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS) for most outcomes, except for some of the mortality and health outcomes (which are at the individual level). Probit APEs are reported for binary outcomes. Robust standard errors are in parentheses and are calculated using replicate weights.

Table A2. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (CIPM)

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
Permanent Income (CPS & SIPP)					
CPS	**24,140*** **	**(5,377)**	**24,430**	**98,090**	**–**
SIPP	**17,800*** **	**(3,461)**	**24,850**	**92,930**	**–**
Years of Education (CPS & SIPP)					
CPS	**0.5730*** **	**(0.1610)**	**11.750**	**13.630**	**–**
SIPP	**0.6980** **	**(0.2850)**	**11.930**	**13.700**	**–**
Mortality (CPS & SIPP)					
Died by 2015 (ind.) – *CPS*	-0.0046	(0.0055)	0.048	0.036	–
Died by 2019 (ind.) – *CPS*	-0.0110	(0.0069)	0.088	0.064	–
Died by 2015 (head) – *CPS*	-0.0069	(0.0082)	0.058	0.040	–
Died by 2019 (head) – *CPS*	**-0.0247** **	**(0.0116)**	**0.109**	**0.071**	**–**
Died by 2015 (ind.) – *SIPP*	0.0035	(0.0114)	0.052	0.041	+
Died by 2019 (ind.) – *SIPP*	-0.0037	(0.0115)	0.078	0.069	–
Died by 2015 (head) – *SIPP*	0.0235	(0.0215)	0.060	0.047	+
Died by 2019 (head) – *SIPP*	**0.0209**	**(0.0220)**	**0.088**	**0.080**	**+**
Health Problems (CPS & SIPP)					
Poor/Fair Health Quality (ind.) – *CPS*	**-0.0683*** **	**(0.0147)**	**--**	**--**	**–**
Poor/Fair Health Quality (head) – *CPS*	-0.0863***	(0.0238)	--	--	–
Poor/Fair Health Quality (ind.) – *SIPP*	**-0.0372** **	**(0.0142)**	**0.181**	**0.104**	**–**
Poor/Fair Health Quality (head) – *SIPP*	-0.0793**	(0.0320)	0.254	0.136	–
Health Condition Limits Work – *SIPP*	-0.0333**	(0.0146)	0.162	0.089	–
Health Condition Prevents Work – *SIPP*	-0.0214*	(0.0121)	0.122	0.056	–
Material Hardships (SIPP)					
Total Number	**-0.1830**	**(0.1510)**	**1.280**	**0.645**	**–**
Did Not Meet All Essential Expenses	-0.0537	(0.0399)	0.346	0.179	–
Did Not Pay Full Rent	-0.0065	(0.0342)	0.160	0.093	–
Evicted Because of Rent	-0.0054	(0.0109)	0.017	0.005	–
Did Not Pay Full Energy Bill	-0.0387	(0.0380)	0.242	0.121	–
Had Energy Cut Off	-0.0259	(0.0180)	0.053	0.020	–
Had Telephone Service Cut Off	-0.0292	(0.0260)	0.095	0.042	–
Needed to See Doctor but Could Not	-0.0339	(0.0318)	0.166	0.084	–
Needed to See Dentist but Could Not	-0.0392	(0.0315)	0.202	0.102	–
Home Quality Problems (SIPP)					
Total Number	**-0.1560** **	**(0.0747)**	**0.410**	**0.225**	**–**
Pests	-0.0627**	(0.0243)	0.157	0.080	–
Leaking Roof	-0.0497**	(0.0250)	0.091	0.051	–
Broken Windows	-0.0065	(0.0186)	0.050	0.031	–
Electrical Problems	0.0041	(0.0085)	0.009	0.007	+
Plumbing Problems	-0.0193	(0.0181)	0.049	0.019	–
Holes or Cracks in Wall	-0.0144	(0.0172)	0.046	0.029	–
Holes in Floor	-0.0096**	(0.0047)	0.008	0.007	–

Table A2. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (CIPM) – cont.

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
Appliances (SIPP)					
Total Number	**-0.2300**	**(0.1620)**	**6.273**	**6.992**	**+**
Microwave	0.0230	(0.0226)	0.940	0.976	–
Dishwasher	0.0930**	(0.0381)	0.429	0.711	–
Air Conditioning	-0.0932**	(0.0364)	0.858	0.887	+
Television	0.0195	(0.0159)	0.973	0.985	–
Personal Computer	0.1030**	(0.0419)	0.624	0.795	–
Washing Machine	-0.2250***	(0.0355)	0.858	0.880	+
Dryer	-0.1740***	(0.0423)	0.811	0.859	+
Cell Phone	0.0972***	(0.0290)	0.781	0.900	–
Assets (SIPP)					
Total Wealth	**61,530****	**(24,980)**	**29,120**	**386,300**	**–**
Total Debt	35,450***	(8,693)	22,330	112,900	+
Net Worth	26,070	(26,820)	6,785	273,500	–
Home Equity	505	(6,785)	19,100	114,000	–
Vehicle Equity	867	(581)	3,062	7,324	–
Other Assets	60,150***	(21,320)	6,957	265,000	–
Food Security Problems (SIPP)					
Total Number	**-0.2110***	**(0.1280)**	**0.948**	**0.459**	**–**
Not Enough Food	-0.0312	(0.0189)	0.061	0.026	–
Food Bought Did Not Last	-0.0624	(0.0393)	0.284	0.146	–
Could Not Afford Balanced Meals	-0.0588	(0.0361)	0.258	0.129	–
Children Not Eating Enough	0.0101	(0.0188)	0.040	0.032	+
Cut Size or Skipped Meals	-0.0529**	(0.0241)	0.128	0.053	–
Ate Less Than Felt One Should	-0.0451*	(0.0260)	0.129	0.058	–
Did Not Eat for Whole Day	-0.0252	(0.0165)	0.048	0.015	–
Public Services and Safety (SIPP)					
Total Num. of Public Service Problems	**-0.0694**	**(0.1390)**	**1.332**	**0.950**	**–**
Inadequate Public Transportation	-0.1270***	(0.0356)	0.299	0.207	–
Afraid to Walk Alone at Night	0.0362	(0.0337)	0.249	0.202	+
Carry Anything When Going Out	-0.0082	(0.0166)	0.067	0.061	–
Public Services Undesirable	0.0189	(0.0204)	--	0.019	+
Unsatisfied with Fire Department	--	--	0.040	0.014	--
Unsatisfied with Hospitals	-0.0365	(0.0228)	0.110	0.064	–
Unsatisfied with Police	-0.0148	(0.0205)	0.094	0.051	–
Unsatisfied with Public Schools	-0.0251	(0.0218)	0.081	0.050	–
Unsatisfied with Public Services	-0.0264	(0.0214)	0.073	0.047	–
Stayed at Home for Safety Reasons	0.0345	(0.0296)	0.141	0.102	+
Take Someone with You for Safety	0.0585**	(0.0293)	0.096	0.089	+
Threat of Crime Enough that Would Move	0.0182	(0.0202)	0.048	0.045	+

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table reports coefficient on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic CIPM poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. Summary measures for each domain are bolded. The sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS) for most outcomes, except for some of the mortality and health outcomes (which are at the individual level). Probit APEs are reported for binary outcomes. Robust standard errors are in parentheses and are calculated using replicate weights.

Table A3. Appliances of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (With and Without Temperature and Single Family Home Controls)

Appliances	With Regular Controls			+ Temp. and Single Family Controls		
	Point Estimate (1)	Standard Error (2)	Supports Geog Adj? (3)	Point Estimate (4)	Standard Error (5)	Supports Geog Adj? (6)
			A. Supplemental Poverty Measure (SPM)			
Total Number	-0.1900	(0.1660)	+	0.179	(0.1590)	–
Microwave	-0.0070	(0.0210)	+	0.0046	(0.0204)	–
Dishwasher	0.0584	(0.0371)	–	0.0822**	(0.0357)	–
Air Conditioning	-0.1750***	(0.0327)	+	-0.0401	(0.0308)	+
Television	0.0023	(0.0173)	–	0.0123	(0.0191)	–
Personal Computer	0.1440***	(0.0404)	–	0.0868**	(0.0409)	–
Washing Machine	-0.1560***	(0.0317)	+	-0.0528*	(0.0315)	+
Dryer	-0.1160***	(0.0390)	+	-0.0139	(0.0358)	+
Cell Phone	0.1110***	(0.0313)	–	0.1000***	(0.0309)	–
			B. Comprehensive Income Poverty Measure (CIPM)			
Total Number	-0.2300	(0.1620)	+	0.0717	(0.1600)	–
Microwave	0.0230	(0.0226)	–	0.0314	(0.0216)	–
Dishwasher	0.0930**	(0.0381)	–	0.1080***	(0.0391)	–
Air Conditioning	-0.0932**	(0.0364)	+	0.0148	(0.0358)	–
Television	0.0195	(0.0159)	–	0.0253*	(0.0153)	–
Personal Computer	0.1030**	(0.0419)	–	0.0484	(0.0411)	–
Washing Machine	-0.2250***	(0.0355)	+	-0.1490***	(0.0375)	+
Dryer	-0.1740***	(0.0423)	+	-0.0916**	(0.0431)	+
Cell Phone	0.0972***	(0.0290)	–	0.0850***	(0.0283)	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of appliance ownership indicators on geographic poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. Panel (a) relies on the SPM and Panel (b) relies on the CIPM. Columns (1)-(3) show estimates with our main set of covariates. Columns (4)-(6) show estimates adding two additional covariates: average monthly temperatures at the county level and proportion of single family homes by county (taken from the ACS). Probit APEs are reported for binary outcomes. Robust standard errors are in parentheses and are calculated using replicate weights.

Table A4. Shares and Counts by Geographic SPM Poverty Category (Additional Analyses)

Poverty Category	CPS Weighted Share of Inds. (1)	CPS Sample Size (Inds.) (2)	CPS Sample Size (Fams.) (3)	SIPP Weighted Share of Inds. (4)	SIPP Sample Size (Inds.) (5)	SIPP Sample Size (Fams.) (6)
A. Regional Price Parities						
Never Poor	0.8368	174,000	65,000	0.8333	73,500	29,000
Non-Geographic-Only Poor	0.0122	2,400	1,000	0.0157	1,500	650
Geographic-Only Poor	0.0122	2,600	1,000	0.0157	1,300	450
Always Poor	0.1388	26,500	11,500	0.1353	12,000	5,600
B. Deep Poverty (MRI)						
Never Deep Poor	0.9279	191,000	72,500	0.9280	82,000	32,500
Non-Geog-Only Deep Poor	0.0051	1,000	400	0.0049	500	200
Geog-Only Deep Poor	0.0051	1,000	400	0.0050	400	150
Always Deep Poor	0.0619	11,500	5,500	0.0621	5,500	2,800
C. Near Poverty (MRI)						
Never Near Poor	0.7294	151,000	56,500	0.7275	63,500	25,500
Non-Geog-Only Near Poor	0.0246	5,300	2,000	0.0265	2,600	1,000
Geog-Only Near Poor	0.0246	5,300	1,900	0.0265	2,200	750
Always Near Poor	0.2214	43,500	18,000	0.2195	19,500	8,600

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table shows the weighted share of individuals and the unweighted number of individuals and sharing units in each of our four geographic poverty categories for the SPM in both the CPS and SIPP. Panel (a) uses Regional Price Parities (RPPs) rather than the Median Rent Index (MRI) to adjust poverty thresholds for geographic variation in cost-of-living, while Panels (b) and (c) use deep and near poverty thresholds adjusted using the MRI. Poverty rates in Panel (a) are anchored to 15.1%, which is the official rate in the CPS. Rates for deep poverty (i.e., below 50% of the poverty line) are anchored to 6.7%, and rates for near poverty (i.e., below 150% of the poverty line) are anchored to 24.6%. These rates correspond to what we obtain using pre-tax money income in the CPS for reference year 2010. The sample for the SPM estimates consists of all individuals, weighted using original survey weights. The sample for the CIPM estimates in the CPS consists of all individuals in sharing units where at least one member has a PIK and no member is whole imputed, weighted using individual survey weights adjusted for non-PIKing and whole imputes (at the sharing unit level). The sample for the CIPM estimates in the SIPP consists of all individuals in sharing units where at least one member has a PIK, weighted using individual survey weights adjusted for non-PIKing (at the sharing unit level).

Table A5. Shares and Counts by Geographic CIPM Poverty Category (Additional Analyses)

Poverty Category	CPS Weighted Share of Inds. (1)	CPS Sample Size (Inds.) (2)	CPS Sample Size (Fams.) (3)	SIPP Weighted Share of Inds. (4)	SIPP Sample Size (Inds.) (5)	SIPP Sample Size (Fams.) (6)
			A. Regional Price Parities			
Never Poor	0.8345	144,000	54,000	0.8338	71,000	28,000
Non-Geographic-Only Poor	0.0145	2,400	950	0.0151	1,500	600
Geographic-Only Poor	0.0145	2,500	900	0.0151	1,200	450
Always Poor	0.1365	21,500	8,800	0.1359	11,000	5,000
			B. Deep Poverty (MRI)			
Never Deep Poor	0.9266	159,000	59,500	0.9265	79,000	31,500
Non-Geog-Only Deep Poor	0.0064	1,000	450	0.0065	600	250
Geog-Only Deep Poor	0.0064	1,000	350	0.0066	500	200
Always Deep Poor	0.0606	8,900	4,000	0.0604	4,800	2,200
			C. Near Poverty (MRI)			
Never Near Poor	0.7330	126,000	47,500	0.7356	62,500	25,000
Non-Geog-Only Near Poor	0.0210	4,000	1,400	0.0185	1,800	650
Geog-Only Near Poor	0.0210	3,700	1,300	0.0184	1,500	500
Always Near Poor	0.2250	36,500	14,000	0.2275	19,500	7,800

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table shows the weighted share of individuals and the unweighted number of individuals and sharing units in each of our four geographic poverty categories for the CIPM in both the CPS and SIPP. Panel (a) uses Regional Price Parities (RPPs) rather than the Median Rent Index (MRI) to adjust poverty thresholds for geographic variation in cost-of-living, while Panels (b) and (c) use deep and near poverty thresholds adjusted using the MRI. Poverty rates in Panel (a) are anchored to 15.1%, which is the official rate in the CPS. Rates for deep poverty (i.e., below 50% of the poverty line) are anchored to 6.7%, and rates for near poverty (i.e., below 150% of the poverty line) are anchored to 24.6%. These rates correspond to what we obtain using pre-tax money income in the CPS for reference year 2010. The sample for the SPM estimates consists of all individuals, weighted using original survey weights. The sample for the CIPM estimates in the CPS consists of all individuals in sharing units where at least one member has a PIK and no member is whole imputed, weighted using individual survey weights adjusted for non-PIKing and whole imputes (at the sharing unit level). The sample for the CIPM estimates in the SIPP consists of all individuals in sharing units where at least one member has a PIK, weighted using individual survey weights adjusted for non-PIKing (at the sharing unit level).

Table A6. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor Using RPP Adjustments

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	26,230***	(7,985)	27,380	98,090	–
Permanent Income (*SIPP*)	17,310***	(4,074)	34,050	92,930	–
Years of Education (*CPS*)	0.4720***	(0.1650)	11.900	13.640	–
Years of Education (*SIPP*)	0.6370***	(0.2360)	12.090	13.700	–
Head Died by 2019 (*CPS*)	-0.0266	(0.0164)	0.130	0.071	–
Head Died by 2019 (*SIPP*)	-0.0229	(0.0185)	0.121	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0558***	(0.0153)	0.230	0.118	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0729***	(0.0149)	0.189	0.103	–
Number of Material Hardships (*SIPP*)	-0.2410*	(0.1320)	1.157	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.0908	(0.0641)	0.349	0.224	–
Number of Appliances (*SIPP*)	-0.3240**	(0.1460)	6.271	6.988	+
Total Wealth (*SIPP*)	97,360**	(46,300)	74,900	384,900	–
Number of Food Security Problems (*SIPP*)	-0.2430*	(0.1260)	0.992	0.460	–
Number of Public Service Problems (*SIPP*)	-0.0078	(0.1430)	--	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	22,160***	(5,632)	24,860	98,090	–
Permanent Income (*SIPP*)	15,030***	(3,426)	24,990	92,930	–
Years of Education (*CPS*)	0.7800***	(0.1430)	11.730	13.630	–
Years of Education (*SIPP*)	0.4950*	(0.2930)	11.930	13.700	–
Head Died by 2019 (*CPS*)	-0.0197*	(0.0112)	0.100	0.071	–
Head Died by 2019 (*SIPP*)	-0.0085	(0.0188)	0.097	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0648***	(0.0149)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0361**	(0.0151)	0.182	0.104	–
Number of Material Hardships (*SIPP*)	-0.2930**	(0.1390)	1.270	0.645	–
Number of Home Quality Problems (*SIPP*)	-0.1090	(0.0718)	0.401	0.225	–
Number of Appliances (*SIPP*)	-0.3590**	(0.1530)	6.256	6.992	+
Total Wealth (*SIPP*)	58,590***	(21,630)	26,340	386,300	–
Number of Food Security Problems (*SIPP*)	-0.2910**	(0.1130)	0.975	0.459	–
Number of Public Service Problems (*SIPP*)	-0.0810	(0.1540)	--	0.950	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. These estimates use Regional Price Parities (RPPs) rather than the Median Rent Index (MRI) to adjust poverty thresholds for geographic variation in cost-of-living. See Table 3 notes for more details.

Table A7. Well-Being of the Geographic-Only Deep Poor Relative to the Non-Geographic-Only Deep Poor

Well-Being Indicators	Point Estimate	Standard Error	Mean for Non-Geog Poor	Overall Mean	Supports Geog Adj? (+/-)
	(1)	(2)	(3)	(4)	(5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	19,270***	(6,748)	27,840	98,620	–
Permanent Income (*SIPP*)	7,228	(7,340)	29,770	92,930	–
Years of Education (*CPS*)	1.2130***	(0.2600)	11.420	13.640	–
Years of Education (*SIPP*)	0.7400**	(0.3700)	11.530	13.700	–
Head Died by 2019 (*CPS*)	0.0076	(0.0294)	0.108	0.071	+
Head Died by 2019 (*SIPP*)	-0.0058	(0.0399)	0.131	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0527**	(0.0212)	0.218	0.118	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0793***	(0.0265)	0.194	0.103	–
Number of Material Hardships (*SIPP*)	-0.4430*	(0.2330)	1.528	0.646	–
Number of Home Quality Problems (*SIPP*)	0.0338	(0.1440)	0.475	0.224	+
Number of Appliances (*SIPP*)	-0.3480*	(0.2050)	6.053	6.988	+
Total Wealth (*SIPP*)	27,860	(48,670)	92,390	384,900	–
Number of Food Security Problems (*SIPP*)	-0.3270	(0.2350)	1.027	0.460	–
Number of Public Service Problems (*SIPP*)	-0.2920	(0.2230)	--	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	22,260***	(6,690)	19,050	98,090	–
Permanent Income (*SIPP*)	21,230***	(6,977)	17,080	92,930	–
Years of Education (*CPS*)	0.4280*	(0.2490)	11.700	13.630	–
Years of Education (*SIPP*)	0.3410	(0.3760)	11.560	13.700	–
Head Died by 2019 (*CPS*)	-0.0491**	(0.0210)	0.123	0.071	–
Head Died by 2019 (*SIPP*)	-0.0912***	(0.0325)	0.163	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0851***	(0.0229)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.1010***	(0.0224)	0.211	0.104	–
Number of Material Hardships (*SIPP*)	0.0152	(0.2390)	1.393	0.645	+
Number of Home Quality Problems (*SIPP*)	-0.0610	(0.1090)	0.433	0.225	–
Number of Appliances (*SIPP*)	0.1630	(0.2850)	5.709	6.992	–
Total Wealth (*SIPP*)	41,220	(33,480)	22,160	386,300	–
Number of Food Security Problems (*SIPP*)	-0.0473	(0.2610)	1.152	0.459	–
Number of Public Service Problems (*SIPP*)	-0.00463	(0.234)	--	0.950	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table reports coefficients on an indicator for being geographic-only deep poor (vs. non-geographic-only deep poor) from regressions of well-being indicators on geographic deep poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. See Table 3 notes for more details.

Table A8. Well-Being of the Geographic-Only Near Poor Relative to the Non-Geographic-Only Near Poor

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	20,610***	(3,398)	37,170	98,620	–
Permanent Income (*SIPP*)	10,880*	(6,327)	37,990	92,930	–
Years of Education (*CPS*)	0.3530***	(0.1080)	12.420	13.630	–
Years of Education (*SIPP*)	0.6350***	(0.1740)	12.450	13.700	–
Head Died by 2019 (*CPS*)	-0.0253***	(0.0092)	0.108	0.071	–
Head Died by 2019 (*SIPP*)	-0.0124	(0.0150)	0.098	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0384***	(0.0098)	0.154	0.118	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0481***	(0.0123)	0.163	0.103	–
Number of Material Hardships (*SIPP*)	-0.1710*	(0.1010)	1.000	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.0412	(0.0389)	0.268	0.224	–
Number of Appliances (*SIPP*)	-0.1950*	(0.1060)	6.526	6.988	+
Total Wealth (*SIPP*)	100,400***	(25,630)	85,080	384,900	–
Number of Food Security Problems (*SIPP*)	-0.0401	(0.0732)	0.611	0.460	–
Number of Public Service Problems (*SIPP*)	-0.0114	(0.1200)	--	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	14,220***	(2,792)	33,340	98,090	–
Permanent Income (*SIPP*)	15,220***	(2,709)	35,940	92,930	–
Years of Education (*CPS*)	0.3830**	(0.1550)	12.390	13.630	–
Years of Education (*SIPP*)	0.2970	(0.2180)	12.520	13.700	–
Head Died by 2019 (*CPS*)	-0.0014	(0.0106)	0.088	0.071	–
Head Died by 2019 (*SIPP*)	-0.0164	(0.0138)	0.083	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0164	(0.0112)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0317**	(0.0121)	0.139	0.104	–
Number of Material Hardships (*SIPP*)	-0.1930	(0.1180)	1.084	0.645	–
Number of Home Quality Problems (*SIPP*)	-0.0822	(0.0592)	0.326	0.225	–
Number of Appliances (*SIPP*)	-0.3360***	(0.1050)	6.599	6.992	+
Total Wealth (*SIPP*)	77,120***	(23,380)	48,800	386,300	–
Number of Food Security Problems (*SIPP*)	0.0656	(0.1230)	0.719	0.459	+
Number of Public Service Problems (*SIPP*)	0.0546	(0.1400)	--	0.950	+

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table reports coefficients on an indicator for being geographic-only near poor (vs. non-geographic-only near poor) from regressions of well-being indicators on geographic near poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. See Table 3 notes for more details.

Table A9. Well-Being of the Geographic-Only OPM Poor Relative to the Non-Geographic-Only OPM Poor

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
Permanent Income (*CPS*)	19,420***	(3,801)	--	98,620	–
Permanent Income (*SIPP*)	16,480***	(4,418)	--	92,930	–
Years of Education (*CPS*)	0.443**	(0.2060)	--	13.640	–
Years of Education (*SIPP*)	0.124	(0.3310)	--	13.700	–
Head Died by 2019 (*CPS*)	-0.0534***	(0.0175)	--	0.071	–
Head Died by 2019 (*SIPP*)	-0.0305	(0.0241)	--	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0334	(0.0257)	--	0.166	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0935***	(0.0325)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1530	(0.1420)	--	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.1170	(0.0815)	--	0.224	–
Number of Appliances (*SIPP*)	-0.2190	(0.2130)	--	6.988	+
Total Wealth (*SIPP*)	21,910	(34,990)	--	384,900	–
Number of Food Security Problems (*SIPP*)	-0.0473	(0.1630)	--	0.460	–
Number of Public Service Problems (*SIPP*)	0.0499	(0.1740)	--	0.949	+

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. We classify individuals as being in poverty using the Official Poverty Measure (OPM). See Table 3 notes for more details.

Table A10. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (Fewer Covariates)

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	19,770***	(6,480)	--	98,620	–
Permanent Income (*SIPP*)	8,537**	(3,338)	--	92,930	–
Years of Education (*CPS*)	-0.1410	(0.1560)	--	13.640	+
Years of Education (*SIPP*)	-0.3100	(0.2840)	--	13.700	+
Head Died by 2019 (*CPS*)	-0.0298**	(0.0140)	--	0.071	–
Head Died by 2019 (*SIPP*)	-0.0300*	(0.0169)	--	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0616***	(0.0215)	--	0.166	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.1390***	(0.0352)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1130	(0.1410)	--	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.1180*	(0.0675)	--	0.224	–
Number of Appliances (*SIPP*)	-0.4080**	(0.1590)	--	6.988	+
Total Wealth (*SIPP*)	28,610	(46,030)	--	384,900	–
Number of Food Security Problems (*SIPP*)	-0.1180	(0.1200)	--	0.460	–
Number of Public Service Problems (*SIPP*)	-0.0148	(0.1350)	--	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	11,620**	(4,722)	--	98,090	–
Permanent Income (*SIPP*)	3,134	(2,073)	--	92,930	–
Years of Education (*CPS*)	-0.0235	(0.1780)	--	13.630	+
Years of Education (*SIPP*)	-0.2540	(0.3040)	--	13.700	+
Head Died by 2019 (*CPS*)	-0.0300**	(0.0117)	--	0.071	–
Head Died by 2019 (*SIPP*)	0.0108	(0.0212)	--	0.080	+
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0761***	(0.0240)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0676**	(0.0332)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1240	(0.1540)	--	0.645	–
Number of Home Quality Problems (*SIPP*)	-0.1440*	(0.0756)	--	0.225	–
Number of Appliances (*SIPP*)	-0.4780***	(0.1580)	--	6.992	+
Total Wealth (*SIPP*)	-16,600	(19,980)	--	386,300	+
Number of Food Security Problems (*SIPP*)	-0.1390	(0.1320)	--	0.459	–
Number of Public Service Problems (*SIPP*)	-0.0006	(0.1420)	--	0.950	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic poverty categories and a limited set of covariates. For permanent income, education, and mortality, the regressions control for age, for assets the regressions control for age and unit size, while for all other outcomes the regressions control for unit size. See Table 3 notes for more details.

Table A11. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (Controlling for Region)

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	23,370***	(8,592)	--	98,620	–
Permanent Income (*SIPP*)	7,846*	(4,043)	--	92,930	–
Years of Education (*CPS*)	0.2480*	(0.1400)	--	13.640	–
Years of Education (*SIPP*)	0.3940*	(0.2220)	--	13.700	–
Head Died by 2019 (*CPS*)	-0.0148	(0.0141)	--	0.071	–
Head Died by 2019 (*SIPP*)	-0.0217	(0.0167)	--	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0480**	(0.0219)	--	0.166	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.1270***	(0.0334)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1480	(0.1370)	--	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.1370**	(0.0649)	--	0.224	–
Number of Appliances (*SIPP*)	-0.0333	(0.1590)	--	6.988	–
Total Wealth (*SIPP*)	133,600**	(51,860)	--	384,900	–
Number of Food Security Problems (*SIPP*)	-0.1750	(0.1230)	--	0.460	–
Number of Public Service Problems (*SIPP*)	-0.0527	(0.1300)	--	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	19,080**	(8,698)	--	98,090	–
Permanent Income (*SIPP*)	9,527**	(3,860)	--	92,930	–
Years of Education (*CPS*)	0.4020**	(0.1640)	--	13.630	–
Years of Education (*SIPP*)	0.5490*	(0.2850)	--	13.700	–
Head Died by 2019 (*CPS*)	-0.0176	(0.0117)	--	0.071	–
Head Died by 2019 (*SIPP*)	0.0253	(0.0224)	--	0.080	+
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0729***	(0.0240)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0312**	(0.0146)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1760	(0.1510)	--	0.645	–
Number of Home Quality Problems (*SIPP*)	-0.1680**	(0.0741)	--	0.225	–
Number of Appliances (*SIPP*)	-0.0902	(0.1550)	--	6.992	+
Total Wealth (*SIPP*)	95,620***	(34,860)	--	386,300	–
Number of Food Security Problems (*SIPP*)	-0.2120*	(0.1270)	--	0.459	–
Number of Public Service Problems (*SIPP*)	-0.0875	(0.1370)	--	0.950	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. We additionally control for binary variables corresponding to each of four geographic regions (Northeast, Midwest, South, West). See Table 3 notes for more details.

Table A12. Well-Being of the Geographic-Only Poor Relative to the Non-Geographic-Only Poor (Controlling for Rural)

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
		A. Supplemental Poverty Measure (SPM)			
Permanent Income (*CPS*)	16,740**	(6,992)	--	98,620	–
Permanent Income (*SIPP*)	1,068	(4,241)	--	92,930	–
Years of Education (*CPS*)	0.1370	(0.1400)	--	13.640	–
Years of Education (*SIPP*)	0.1170	(0.2100)	--	13.700	–
Head Died by 2019 (*CPS*)	-0.0203	(0.0140)	--	0.071	–
Head Died by 2019 (*SIPP*)	-0.0213	(0.0165)	--	0.080	–
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0507**	(0.0221)	--	0.166	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.1150***	(0.0340)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1170	(0.1380)	--	0.646	–
Number of Home Quality Problems (*SIPP*)	-0.0979	(0.0639)	--	0.224	–
Number of Appliances (*SIPP*)	-0.3260**	(0.1550)	--	6.988	+
Total Wealth (*SIPP*)	1,061	(50,590)	--	384,900	–
Number of Food Security Problems (*SIPP*)	-0.1500	(0.1230)	--	0.460	–
Number of Public Service Problems (*SIPP*)	-0.0182	(0.1290)	--	0.949	–
		B. Comprehensive Income Poverty Measure (CIPM)			
Permanent Income (*CPS*)	12,650**	(5,022)	--	98,090	–
Permanent Income (*SIPP*)	1,506	(3,811)	--	92,930	–
Years of Education (*CPS*)	0.2960*	(0.1610)	--	13.630	–
Years of Education (*SIPP*)	0.2430	(0.2870)	--	13.700	–
Head Died by 2019 (*CPS*)	-0.0229*	(0.0117)	--	0.071	–
Head Died by 2019 (*SIPP*)	0.0257	(0.0224)	--	0.080	+
Ind. Has Poor/Fair Health Quality (*CPS*)	-0.0775***	(0.0239)	--	--	–
Ind. Has Poor/Fair Health Quality (*SIPP*)	-0.0515	(0.0313)	--	0.136	–
Number of Material Hardships (*SIPP*)	-0.1460	(0.1510)	--	0.645	–
Number of Home Quality Problems (*SIPP*)	-0.1330*	(0.0756)	--	0.225	–
Number of Appliances (*SIPP*)	-0.3660**	(0.1540)	--	6.992	+
Total Wealth (*SIPP*)	-35,010	(31,370)	--	386,300	+
Number of Food Security Problems (*SIPP*)	-0.1880	(0.1260)	--	0.459	–
Number of Public Service Problems (*SIPP*)	-0.0610	(0.1400)	--	0.950	–

*** p<0.01, ** p<0.05, * p<0.1

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data

Notes: This table reports coefficients on an indicator for being geographic-only poor (vs. non-geographic-only poor) from regressions of well-being indicators on geographic poverty categories and covariates including age, gender, marital status, unit type, and race/ethnicity. We additionally control for a binary variable corresponding to rural (non-metropolitan) status. See Table 3 notes for more details.

Table A13. Regression Estimates of Mobility Outcomes on Median Rent

Mobility Outcomes (Conditional on Parent Income at 25th Percentile)	Point Estimate (1)	Standard Error (2)	Observations (3)
Tract-Level			
Household Income at Age 35	7.490***	(0.0873)	70,834
Individual Income (Excluding Spouse) at Age 35	5.350***	(0.0445)	
County-Level			
Household Income at Age 35	4.974***	(0.517)	3,134
Individual Income (Excluding Spouse) at Age 35	5.498***	(0.313)	
Commuting Zone-Level			
Household Income at Age 35	2.479**	(0.989)	739
Individual Income (Excluding Spouse) at Age 35	4.513***	(0.536)	
CBSA-Level			
Household Income at Age 35	5.519***	(1.581)	323
Individual Income (Excluding Spouse) at Age 35	7.391***	(1.094)	

*** p<0.01, ** p<0.05, * p<0.1

Data: Opportunity Atlas, 2009-2011 CPS ASEC
Notes: This table shows the coefficients from regressions of two mobility outcomes (household income at age 35 and individual income at age 35, each conditional on having parents in the 25th percentile of income) on median rent. The mobility outcomes are estimated or individuals born between 1978 and 1983. The outcomes and rent levels are all in thousands. For regressions at the tract-, county-, and community zone-level, the median rent levels are for 2012-2016 and obtained from the Opportunity Atlas. For regressions at the CBSA-level, the median rent levels are for 2008-2010 and obtained from the 2009-2011 CPS ASEC. All regressions are weighted using the population of a given geographic area (tract, county, commuting zone, or CBSA) in 2010. Heteroskedastic-robust standard errors are in parentheses.