The Geography of Disadvantage: Implications for Poverty Assessment and Program Targeting

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Abstract

Individuals are often thought to be more disadvantaged in higher-cost areas. As a result, geographic adjustments for local prices are embedded in many federal payments to states, localities, and individuals and have been proposed or implemented for various poverty measures. This paper proposes a rigorous approach to assess the desirability of geographic adjustments to poverty measures by examining how well they achieve a central objective of a poverty measure: identifying the least advantaged population. Specifically, we compare an exhaustive list of material well-being indicators of those classified as poor under the Supplemental Poverty Measure and the new Comprehensive Income Poverty Measure with and without a geographic adjustment. These well-being indicators are drawn from linked survey and administrative records and include material hardships, appliances owned, home quality issues, food security, public services, health, education, assets, permanent income, and mortality. For nine of the ten domains of well-being indicators, we find that incorporating a geographic adjustment identifies a less deprived poor population. This result can be explained by local prices being positively correlated with public goods and locational amenities, which are valued by those with low incomes.

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1. Introduction

Where in the United States are individuals the most disadvantaged? Answers to this question can have enormous policy implications, not least because government programs frequently target certain geographic areas for funding. Programs like Title I (Department of Education) and Opportunity Zones allocate funds based on local poverty rates. Other programs, such as Empowerment Zones and Community Development Block Grants, target areas along additional dimensions like unemployment rate and housing supply. At the individual level, current federal policy also differentiates between geographic areas in both benefit levels and reimbursement rates. For example, maximum benefit amounts for the Supplemental Nutrition Assistance Program (SNAP) and reimbursement rates for free and reduced-price school meals are higher in Alaska and Hawaii than in the 48 continental states. Moreover, eligibility and benefits for federal housing assistance are determined based on incomes and fair market rents that vary across metropolitan and non-metropolitan areas.

In assessing where deprivation is most pronounced, a common answer focuses on places where conventionally-measured prices, specifically housing costs, are highest. For example, in FY 2021, the median rent paid for a 2-bedroom apartment in New York City is $2,263, more than three times as large as the median rent paid for a 2-bedroom apartment in rural Mississippi ($684).[1] Given these differences, should an individual that lives in New York City be considered "poorer" than someone with the same nominal income in rural Mississippi? In other words, should poverty thresholds should be adjusted to reflect geographic differences in the cost of living? While the Official Poverty Measure (OPM) does not incorporate a geographic adjustment, much of the recent policy literature presumes that geographic adjustments are justified.[2] The Census Bureau's Supplemental Poverty Measure (SPM) adjusts its thresholds for geographic differences in housing prices (Fox 2019). Canada uses low-income cutoffs that vary geographically by city size and urban or rural residence (Baker, Currie, and Schwandt 2019).[3] In classifying fewer people as poor in

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[1] These amounts are derived from the Department of Housing and Urban Development's estimates of the 50th percentile of rent by geographic location. See https://www.huduser.gov/portal/datasets/50per.html#2021.

[2] On more than one occasion, members of Congress – including Rep. Jim McDermott (D-WA) and Sen. Chris Dodd (D-CT) in 2009 and Rep. Alexandria Ocasio-Cortez (D-NY) in 2019 – have introduced bills proposing that the official poverty line in the U.S. be adjusted for geographic variation in cost-of-living. In its "Measuring Poverty" report, the National Academy of Sciences (1995) recommended a number of changes to the OPM, including that "poverty thresholds should be adjusted for differences in the cost of housing across geographic areas of the country" (p. 183).

[3] See also Statistics Canada's page on low-income cutoffs: https://www150.statcan.gc.ca/n1/pub/75f0002m/2012002/lico-sfr-eng.htm

lower-cost areas and more people as poor in higher-cost areas, geographic adjustments to poverty thresholds would sharply change how researchers characterize poverty and how policymakers allocate anti-poverty efforts.

Yet, researchers remain divided as to whether geographic adjustments are conceptually desirable.[4] A long literature in economics suggests that consumers are willing to pay more in certain areas to consume higher-quality amenities (Rosen 1974, Haurin 1980, Roback 1982). As a result, the variation in housing prices across locations may simply reflect spatial variation in public goods and amenities, such as school quality, health care facilities, and employment opportunities (Oates 1969, Epple 2008, Brueckner 2011). Indeed, existing price indices fail to account for a number of characteristics that affect locational desirability and are potentially valued by low-income families. These include not only housing amenities, but also the range of available goods and services (e.g., medical specialists), the time costs of buying goods and services, and public goods that are not purchased (e.g., generosity and accessibility of safety net programs). However, the difficulties of estimating hedonic models make it difficult, if not impossible, to fully account for these characteristics. Omitted variable bias already plagues the identification of marginal values of various amenities (Greenstone 2017); and yet, identifying their average values – which requires even more information – is what is relevant for constructing an appropriate price index.

In this paper, we assess the desirability of geographic adjustments to poverty measures. We do so by examining whether geographic adjustments currently in use – and others that have been proposed – help to achieve what several key studies have deemed to be the central goal of a poverty measure: identifying the most disadvantaged population (see, e.g., Ruggles 1990, National Academy of Sciences 1995).[5] A wide variety of programs determine benefit eligibility based upon either a poverty cutoff or some multiple of a poverty line, constructed using a resource measure that is conceptually similar to that of the Official Poverty Measure (OPM).[6] Consequently, a poverty measure that identifies the most disadvantaged can help to target government transfers to

[4] 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).
[5] For example, the NAS Panel in *Measuring Poverty* sought to produce a "measure that will more accurately identify the poor population today" (p. 1) and went on to define poverty as "material deprivation." (p. 19). Both of the cited sources go on to favor geographic adjustments, at least at some level of geography.
[6] These programs include the Supplemental Nutrition Assistance Program (SNAP), free and reduced-price school meals, Head Start, and the Low Income Home Energy Assistance Program (LIHEAP). For a full list of federal programs that use poverty guidelines in determining eligibility, see https://www.irp.wisc.edu/resources/what-are-poverty-thresholds-and-poverty-guidelines/.

those who are most needy. This goal is also consistent with how researchers and the broader public often think about poverty measures, which are used as indicators of disadvantage and predictors of various negative outcomes. Even if one conceives of being in poverty has having income below some minimum standard, there are statistical difficulties associated with accurately measuring income. Thus, utilizing other indicators of material well-being that are correlated with true income can aid in measuring the truth.

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 of Income and Program Participation (SIPP), thought to have the most accurate U.S. income information. In each survey, we compute both the SPM and the new Comprehensive Income Poverty Measure (CIPM) – the latter of which measures incomes more accurately using linked survey and administrative data from the Comprehensive Income Dataset (CID) Project – with and without a geographic adjustment.[7] To compare different poverty measures on an equal footing, we keep the share of individuals in poverty under alternative measures the same, proportionately adjusting poverty cutoffs as needed. This can be thought of more generally as comparing well-being levels between high- and low-cost areas, holding measures of nominal income constant. We analyze a wide variety of well-being measures from survey and administrative sources, including survey reports of material hardships, appliances owned, home quality issues, food security, public services, health, education, and assets, as well as permanent income and mortality from administrative records. In total, we examine 71 well-being indicators spanning these ten domains.

For each of the well-being indicators, we compare those who are poor under a non-geographically-adjusted poverty measure but not the geographically-adjusted version (i.e., the "non-geographic-only poor") to those who are poor under a geographically-adjusted poverty measure but not a non-geographically-adjusted measure (i.e., the "geographic-only poor"). These are the only two groups in a cross-classification of the two poverty definitions that matter for the comparison of the two approaches, as those classified as poor or non-poor by both measures do not enter the comparison. More broadly, this strategy builds upon previous work showing that one can assess the desirability of a change to a poverty adjustment by examining the extent of deprivation among those classified as poor with and without the change (see Meyer and Sullivan 2003, 2011, 2012, Renwick 2018, Fox and Warren 2018, Renwick 2019, Meyer et al. 2021).

[7] In a robustness check, we also compute results using a third poverty measure (OPM).

For nine of the ten domains of well-being indicators that are available, we find that the majority of outcomes (or summary outcome) point to the geographic-only poor being more deprived than the non-geographic-only poor under either the SPM or CIPM. Among eight of these nine domains, at least two measures indicate that geographic adjustments statistically significantly identify a less deprived poor population. These general patterns hold after a variety of extensions and robustness checks, including partial geographic adjustments, using Regional Price Parities (which cover a broader bundle of goods) as the geographic adjustment index, focusing on those switched in and out of deep and near poverty by a geographic adjustment (i.e., holding nominal incomes constant at alternate levels), and using the OPM as the poverty measure.

Our results can be explained by the empirical fact that prices at the state or sub-state level are strongly associated with many characteristics that are important to those with low incomes. Wages have been found to rise almost one for one with prices (DuMond et al. 1999, Hirsch 2011), and we confirm this result in the CPS. Many other characteristics differ across local areas and have been shown to be reflected in home prices or rents. These include public goods such as schools (Tiebout 1956, Oates 1969, Black 1999, Epple 2008), pollution (Davis 2004, Chay and Greenstone 2005), and cash welfare (Glaeser 1998). Many categories of state and local spending are strongly associated with prices. We find that the elasticity of spending with respect to prices exceeds one for state and local expenditures on welfare, elementary and secondary education, environment and housing, and police. These characteristics have the potential to offset the increases in resources needed to maintain a given standard of living in the face of higher prices for some goods. Partly as a result of these patterns, we also 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 along various dimensions. Chetty et al. (2014) investigate the spatial distribution of intergenerational mobility across commuting zones in the United States. Shaefer, Edin, and Nelson (2020) examine the variation across communities in an index of deep disadvantage that comprises measures of income, health, and social mobility. Diamond and Moretti (2021) provide estimates of the standard of living – proxied for by consumption – by commuting zone and ask how they relate to local cost of living. We depart from the existing literature in at least two crucial ways. First, rather than looking at only one or two dimensions of well-being, we investigate as many measures as we can: a broad range of over seventy outcomes spanning ten domains. Second, rather than studying the entire population, we focus on the poor population and use linked survey and administrative data to measure the bottom of the income distribution as accurately as possible.

The remainder of the paper is structured as follows. Section 2 presents a simple theoretical model of how local poverty thresholds should change with local prices and other characteristics, reviews the theoretical literature on the desirability of geographic adjustments, and discusses empirical methods previously used to geographically adjust poverty thresholds. Section 3 describes the survey and administrative data we use and explains how we calculate poverty measures with and without a geographic adjustment. Section 4 presents descriptive statistics showing how poverty rates change after incorporating a geographic adjustment. Section 5 discusses our measures of material well-being and the analytical methods used to compare well-being across poverty measures. Section 6 contains the main regression results comparing material well-being measures among those moved in and out of poverty by a geographic adjustment. Section 7 presents extensions and robustness checks, and Section 8 provides empirical explanations for our main results. Section 9 concludes.

2. Theory and Previous Literature

A Simple Model of Local Poverty Thresholds and Prices

We begin with a simple formal model of how local poverty thresholds should change as local prices change, based on Glaeser (2011). We assume that the goal of poverty assessment is to identify those that are suffering the greatest deprivation, though other goals are possible.[8] Suppose that 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 into indirect utility ($V_Y \geq 0$, $V_{A_j} \geq 0 \; \forall A_j \in \mathbf{A}$), while prices enter negatively ($V_P \leq 0$). For simplicity, we assume in this setting that P is a scalar (e.g., P may be the price for a single good like housing or a composite index of prices for a basket of goods). Following Glaeser (2011), we classify a household as poor if its value of $V(Y, P, \mathbf{A})$ is below that of some minimum deprivation level $\underline{V}$. Let Y_0^* designate the income level in location 0 such that $V(Y_0^*, P_0, \mathbf{A}_0) = \underline{V}$, where P_0 and $\mathbf{A}_0$ are the price and amenity levels in location 0, respectively. In other words, Y_0^* can be thought of as the

[8] 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.

"poverty threshold" in location 0 – i.e., for a given set of prices and amenities in location 0, incomes below (above) Y_0^* will lead to deprivation levels below (above) $\underline{V}$.

Using this setup, we analyze how the appropriate poverty threshold changes as other determinants of utility change. Before proceeding, we make an additional modification to the framework in Glaeser (2011). Namely, we include hourly wages w and unmeasured income N as additional inputs into indirect utility, as they are key determinants of utility that vary geographically. N can include income that is often under-reported in various data sources, such as housing assistance, child support, and workers' compensation. It can also include sources ranging from medical in-kind transfers like Medicaid to uncompensated hospital care and food pantries, which are typically omitted from standard income measures. Note that hourly wages could alternatively be considered an element of a price vector P. Hourly wages and unmeasured income enter positively into indirect utility ($V_w \geq 0, V_N \geq 0$). We can then totally differentiate $V(Y^*, P, \mathbf{A}, w, N) = \underline{V}$ to obtain:

$$V_Y dY^* + V_P dP + \sum_j V_{A_j} dA_j + V_w dw + V_N dN = 0. \tag{1}$$

Rearranging terms and dividing by dP yields:

$$\frac{dY^*}{dP} = -\frac{V_P}{V_Y} - \sum_j \frac{V_{A_j}}{V_Y}\frac{dA_j}{dP} - \frac{V_w}{V_Y}\frac{dw}{dP} - \frac{V_N}{V_Y}\frac{dN}{dP}, \tag{2}$$

which gives an expression for how the appropriate poverty threshold changes as prices change. Using Roy's Identity, we can rewrite equation (2) as follows:

$$\frac{dY^*}{dP} = \underbrace{X}_{\geq 0} - \underbrace{\sum_j \frac{V_{A_j}}{V_Y}\frac{dA_j}{dP}}_{\geq 0} - h\underbrace{\frac{dw}{dP}}_{\geq 0} - \underbrace{\frac{V_N}{V_Y}\frac{dN}{dP}}_{\geq 0}, \tag{3}$$

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. Under these assumptions, the expression on the right side of equation (3) boils down to X. This makes intuitive sense – in the absence of all other terms, higher prices must lead to a higher poverty threshold in order to maintain the same level of consumption. However, the presence of the amenity, wage, and unmeasured income terms will counteract and potentially reverse the naïve price correction. We know from an abundance of evidence that amenities such as school quality and clean air tend to be positively correlated with prices. We also empirically find that areas with higher prices have higher hourly wages and higher levels of non-labor income sources. Thus, if da/dP, dw/dP, and dN/dP are sufficiently positive, then the appropriate poverty threshold Y^* could be decreasing in prices when we allow other factors like amenities, hourly wages, and unmeasured income (which enter positively into utility) to change with prices as well. Importantly, we are not assuming that the spatial equilibrium assumption holds for those near the poverty line (in such a case, increased amenities and hourly wages would exactly offset higher nominal prices). However, it is likely to be the case that local amenities and incomes are strongly correlated with local prices for those in poverty.

Literature on Prices and Amenities Across Geography

A long literature going back nearly seventy years has explored how geographic differences in prices reflect local characteristics. Tiebout (1956) famously argued that a household, under a set of assumptions including costless migration across areas, will sort into a community providing public good levels most closely aligned to its preferences. Oates (1969) built upon Tiebout's argument by reasoning that this type of sorting will result in higher housing prices in areas with higher levels of public goods provision. In arguably the classic approach to spatial equilibrium, Rosen (1974), Haurin (1980), and Roback (1982) demonstrated that wages and rents in equilibrium must adjust so that workers – who are assumed to care about amenities in addition to wages and cost-of-living – are indifferent between living in areas with differing amenity levels. Specifically, in a location with higher amenities, Roback inferred that consumers' willingness to pay for those amenities can be obtained by taking the sum of the higher housing costs and lower wages in that location. While more recent work (see, e.g., Roback 1988, Gyourko and Tracy 1991, Moretti 2011) loosens some of the assumptions in Roback's initial model (allowing labor to be heterogeneous rather than homogeneous, accommodating non-tradable consumption goods in addition to tradable goods, etc.), Roback's original finding remains largely intact: nominal wages and prices adjust to take into account differences in amenities across localities.

In considering the applicability of this approach to the poor, one should recognize that the adjustment of prices to local amenities might be largely determined by the amenities for the larger group of non-poor individuals. For example, the adjustment of prices may not reflect wages in the low-wage labor market or the availability of support through welfare programs available to the least well off. In such a case, one cannot expect price adjustments to make all geographic areas equally desirable to the poor. Migration costs or restrictions on wage adjustments (such as minimum wage laws) could have a similar effect.

To develop an optimal adjustment for differences across localities using the Rosen-Haurin-Roback framework, one would need to account for wages and amenities as well as prices. But even if an approximate equilibrium does not materialize, that framework clarifies the information needed to optimally adjust for geographic differences in prices – namely, all characteristics of geographic areas that affect the desirability of those areas and how they are valued by low-resource families. This requirement is demanding, if not unattainable. One would have to estimate the value of all relevant amenities, which then could be used to construct a price index (Blomquist et al. 1988, Gyourko and Tracy 1991). Empirical implementation has found overwhelming evidence of the presence of amenities, but great difficulty in pinning down their values.[9] Greenstone (2017) argues that the omitted variable problem is so overwhelming that reliable estimates of the marginal value of certain amenities can only be obtained under special circumstances. Furthermore, even if one can obtain the valuation for the marginal person, it is the average valuation that is desired for a price adjustment. Estimating the average is an even harder task (Kaplow 1995, Greenstone 2017). In summary, the canonical economic model of prices and amenities suggests that amenity values are needed to make an appropriate geographic price adjustment, but efforts to empirically implement the model indicate that the current data are inadequate to estimate these values.

Closely related to the geographic adjustment of poverty thresholds, Kaplow (1995) and Glaeser (1998) examine the circumstances under which equity and efficiency are improved by tax and transfer payments that differ across geography. Besides the static changes in well-being from such adjustments, the authors also consider how such geographic differences would be affected by the possible migration of those with few resources. Kaplow (1995) undertakes a conceptual investigation of spatial cost-of-living adjustments in the tax and transfer system. In a benchmark case that leads to equal utility between regions, Kaplow reasons that it would be efficient and

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

equitable to adjust transfers for cost-of-living differences. However, there are certain factors that suggest that cost-of-living adjustments may be undesirable. Principally, when differences in nominal cost-of-living are systematically correlated with differences in amenities across regions, making adjustments using standard price indices may be counterproductive. He also points out that increasing transfers to low-cost areas would reduce government costs if it induces a pattern of migration from high-cost regions to low-cost regions.

Similar to Kaplow (1995), Glaeser (1998) shows that the indexing of transfer payments to local price levels might increase social welfare under the following assumptions: amenities are complements (rather than substitutes) with income, prices are not being offset by higher wages, higher transfer levels do not induce greater mobility to the high transfer areas, and individuals are risk averse. Using his model, Glaeser performs a calibration exercise to calculate the optimal amount of indexing under various parameter values corresponding to his assumptions that are relevant for the transfer recipient population.[10] Under these parameters, Glaeser finds that a one percent increase in prices should optimally lead to a 0.33 percent increase in transfers relative to total income. Notably, under every combination of parameter estimates used to calibrate the model, he finds that this elasticity should never optimally exceed one. In contrast, using data on AFDC (Aid to Families with Dependent Children, the precursor to Temporary Assistance for Needy Families or TANF), Glaeser finds evidence that the elasticity of transfer payments with respect to local prices exceeds 1.5. He uses this result to conclude that the current level of indexing by geography appears to be too strong to be optimal.[11]

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 for a given geographic area is calculated as the ratio of its median gross rent paid for a two-bedroom unit with a complete kitchen and bathroom to the

[10] His preferred estimate assumes that amenities and income are independent (i.e., neither complements nor substitutes), wages are fixed, the elasticity of migration with respect to income is 1, and the coefficient of relative risk aversion is equal to 2 (with the literature suggesting estimates that range from 1 to 10).

[11] While Glaeser analyzes an adjustment that determines all payments (including local payments), our paper focuses on measurement and marginal changes to targeting by the federal government.

median gross rent paid for the same unit type in the U.S. 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 vice-versa). In order to adjust for amenities in a coarse way, Renwick (2018) cuts the variation in the MRI index in half. As Renwick notes, 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 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 two hundred individual items comprising eight broad categories: housing, transportation, food, education, recreation, medical, apparel, and other. Thus, RPPs reflect prices for a wider set of goods and services than the MRI, which only accounts for differences in rents. A final method for incorporating geographic adjustments is to use food, apparel, and rent regional price parities or FAR RPPs (Renwick et al. 2014, Renwick et al. 2017). FAR RPPs cover only the subset of goods in RPPs that are also included in the SPM poverty threshold – namely food, apparel, and rent. Section A1 of the online appendix contains additional details about each of these specific indices.

Existing Evidence on Associations with Deprivation

Several papers have analyzed the desirability of a geographic adjustment by comparing the material deprivation of those classified as poor with and without an adjustment. In a supplementary analysis to their main results, Meyer and Sullivan (2012, see online appendix) analyze the impact of adjusting thresholds for geographic variation in prices on the characteristics of the SPM poor in the CPS. They find that geographically adjusting the thresholds leads to a poor population that is more likely to be covered by private health insurance and has higher levels of education, but the statistical significance of these changes is not examined.

Renwick (2018, 2019) investigates the correlation between poverty rates using various adjustments – i.e., the MRI, RPP, FAR RPP, and rescaled MRI – and measures of material deprivation. Specifically, using 51 observations (50 states plus the District of Columbia), she analyzes the correlation between state poverty rates (averaged across the 2015-17 reference years using the CPS and adjusted using each of the methods above) with the state-level multidimensional deprivation index (MDDI).[12] Renwick finds that three of the geographically adjusted poverty measures are less correlated with the multi-dimensional deprivation index than the measure that does not adjust for cost of living, although tests of significance are not reported for all comparisons. A fourth geographic adjustment is more highly correlated with the well-being indicator than the unadjusted SPM. The winning adjustment is the rescaled MRI based on an ad hoc multiplication of the SPM price adjustment by one-half. When examining the components of the multidimensional measure, most are more correlated with the unadjusted SPM measure than with any of the geographically adjusted measures, although not all comparisons are tested.

The well-being indicators that Renwick uses are broader and the statistical tests stronger than in Meyer and Sullivan (2012). However, the analysis uses state averages rather than individual data. Thus, it is informative about state-level differences in poverty, but it may be less informative for differences by characteristics like family type, race, age, or other geographic levels. The approach also does not keep the poverty rate the same across poverty measures so the measures are not completely comparable, although examining correlations should reduce or eliminate the impact of this non-comparability. Finally, the analysis does not hold constant demographic differences across the states which might confound the comparisons.

In another paper, Baker, Currie, and Schwandt (2019) provide empirical evidence on the relationship between poverty and mortality in Canada. They analyze Canadian poverty using the Canadian low-income cutoff (LICO). While the official version of the LICO uses a geographic adjustment based on the size of the city in which a person lives, they also construct a fixed-cutoff LICO that does not have geographic adjustments. When the authors analyze the relationship between the fixed-cutoff LICO and mortality, they find that areas with more poor people have higher rates of mortality. However, when analyzing the relationship between the official LICO and mortality, they find that, among some age groups, areas with more poor people have lower mortality rates. This counterintuitive result suggests that the geographic adjustment to Canada's LICO does not identify those who are the most deprived.

[12] The MDDI is a state-level measure of deprivation developed by the Census Bureau that combines measures of several components of well-being – including health, poverty, education, economic security, housing, and neighborhood quality (Glassman 2019). Five of the six components are estimated from responses to the ACS, while neighborhood quality is measured using the County Health Rankings and Roadmaps dataset.

Conversely, in a recent paper, Diamond and Moretti (2021) find that low-income residents in more affordable commuting zones have higher levels of consumption than low-income residents in more expensive commuting zones. However, it is worth highlighting several features of their methodology that may rationalize their results. First, they focus on differences in standard of living between commuting zones, which are largely metropolitan. This means that many of those who live in non-metropolitan (rural) areas are omitted from the comparisons, even though low-income individuals who live in such areas may have very different consumption patterns than those who live in a commuting zone. Second, the authors examine a sample of households limited to those with a bank account and annual income above $10,000, meaning many of the lowest-income households in the U.S. (particularly those who are unbanked) are excluded from their analyses. Finally, the authors' main outcome of interest – consumption expenditures tied to bank transactions – may be a more relevant proxy of well-being for those higher up in the distribution than for those at the very bottom. For the latter group, outcomes indicative of deep disadvantage, such as material hardships and mortality risk, may be more revealing proxies for standard of living.

3. Data and Poverty Measures

This section describes the survey and administrative data used and the methods for linking data sources. We then discuss the features of our two core poverty measures – the Supplemental Poverty Measure (SPM) and the Comprehensive Income Poverty Measure (CIPM). In discussing each poverty measure, we focus on its key ingredients – namely, the resource measure, resource-sharing unit, poverty threshold, and equivalence scale used to set poverty thresholds for families that differ in size or composition. 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.

Data

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 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.

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. Specifically, we take as our analysis sample all individuals who appear in reference month 4 of Wave 6 (which spans April-July 2010), incorporate information on survey incomes from other months in 2010 during which these individuals appear, and proportionately scale up survey incomes for the 21% of individuals who are interviewed for only a portion of the year. This decision not only makes the CPS and SIPP income measures more comparable, but it also aligns the SIPP reference period with that of the linked calendar year tax data. 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.

Administrative Data

We also employ a number of administrative data sources. We obtain earnings records from multiple sources of tax records (including Internal Revenue Service (IRS) W-2 Forms, the Detailed Earnings Record (DER) database of the Social Security Administration (SSA), and IRS 1040 Forms), asset income (namely interest and dividends) from IRS 1040 Forms, and retirement distributions from IRS 1099-R forms. We also simulate tax liabilities and credits from line items available on IRS 1040 Forms. We have a number of administrative program participation records from government agencies, covering Social Security, Supplemental Security Income (SSI), Service-Connected Disability payments to veterans, and HUD housing assistance. 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, including using IRS tax records from tax years 2008, 2009, 2011, and 2012 to construct a measure of permanent income and the Social Security Administration's Numident file to calculate mortality rates. Appendix Section A2 contains additional details about the survey and administrative data sources.

Linking Data Sources

We link the survey and administrative data sources using individual identifiers called Protected Identification Keys (PIKs). PIKs are created by the U.S. Census Bureau's Person Identification Validation System (PVS), which is based on a reference file containing Social Security Numbers linked to names, addresses, and dates of birth (Wagner and Layne 2014). Our survey-based analyses use the full CPS or SIPP sample and original survey weights. For most of our analyses looking at outcomes from the administrative data or using CID income as the resource measure, we restrict our sample to individuals whose sharing units have at least one member with a PIK (and, in the CPS, no member that is whole imputed).[13] To account for the bias arising from non-random missing PIKs (and whole imputations in the CPS), we divide survey weights by the predicted probability that at least one member of the sharing unit has a PIK (and no member is whole imputed in the CPS), conditional on observable characteristics in the survey.

Poverty Measures

Supplemental Poverty Measure (SPM)

The Supplemental Poverty Measure (SPM) differs from the Official Poverty Measure (OPM) in several ways. Unlike the OPM, which uses pre-tax money income as its resource measure, the SPM resource measure covers a fuller set of resources available for consumption – namely, 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 estimated expenses for work, childcare, child support, and health care. We calculate the SPM resource measure using survey information only, following the methodologies in Fox (2019) and Short (2014) for the CPS and SIPP, respectively.

Next, 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

[13] 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.

22. The SPM also uses different poverty thresholds than the OPM and adjusts the thresholds in a different way. While the OPM thresholds reflect only economies of scale in food and do not adjust for geographic price differences, the SPM thresholds are based on out-of-pocket spending on a broader set of goods and adjust for geographic differences in rental prices. Formally, the threshold for an SPM unit can be written as the product of the following terms:

$$SPM\ Threshold_{t,ac,sm} = (Base\ Threshold)_t \times \frac{(Equivalence\ Scale\ Factor)_{ac}}{E} \times [(Housing\ Share_t \times MRI_{sm}) + (1 - Housing\ Share_t)], \quad (4)$$

where t is the unit's type of 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 (4) is the base threshold, which is calculated as 1.2 times the average spending on food, shelter, clothing, and utilities of those in the 30^{th}-36^{th} percentiles of spending on these expenses, computed using five years of Consumer Expenditure (CE) Survey data. However, the SPM calculates spending separately for three housing tenure groups using the same percentiles: homeowners with mortgages, homeowners without mortgages, and renters (implicitly assuming they are otherwise the same).[14] The second term is a three-parameter equivalence scale that adjusts the threshold based on the number of adults and children in the reference unit, and we divide it by the equivalence scale for a two-adult, two-child unit (denoted by the constant E).[15] The final term is the geographic adjustment factor, which adjusts the threshold for geographic differences in rental prices using the Median Rent Index (MRI). The MRI is calculated separately for 358 geographic areas, including 264 publicly-identified MSAs, non-metropolitan areas in 48 states, and "other" metropolitan areas in 46 states.[16] The MRI is scaled by the share of expenditures taken up by housing costs, which again varies by housing tenure.[17] For more details of the methods used to construct the SPM, see Appendix Section A3.

[14] In 2010, these spending amounts are $25,018 for homeowners with mortgages, $20,590 for homeowners without mortgages, and $24,391 for renters. See https://www.census.gov/prod/2011pubs/p60-241.pdf.
[15] The three-parameter equivalence scale factor is given by $(adults)^{0.5}$ for units without children, $(adults + 0.8 + 0.5 \times (children - 1))^{0.7}$ for single-parent units, and $(adults + 0.5 \times \text{children})^{0.7}$ for all other units.
[16] Not all states have observations in non-metropolitan areas or other metropolitan areas, leading to less than 50 such adjustment factors for non-metropolitan areas and for other metropolitan areas.
[17] These housing shares are 0.510 for homeowners with mortgages, 0.404 for homeowners without mortgages, and 0.497 for renters. See https://www.census.gov/prod/2011pubs/p60-241.pdf.

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 constructing an alternative resource measure with some conceptual differences from that of the SPM. First, we replace survey reports or imputations of asset income (namely interest and dividends), retirement income, Social Security, SSI, veterans' benefits, and tax liabilities and credits with their counterparts from the administrative data, 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 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). Finally, 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. Because the CPS does not ask about assets in detail, we are only able to estimate these asset flows in the SIPP.

The CIPM uses the same resource unit as the SPM and 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 for distinct housing status groups (which is an implicit way of accounting for differences in available resources).[18]

Additional Methods

To construct the SPM and CIPM without a geographic adjustment, we simply remove the geographic adjustment factor from the poverty threshold, meaning the overall threshold is just the product of the base threshold and equivalence scale. For both the SPM and CIPM (with and without a geographic adjustment), we proportionately adjust thresholds so that the poverty rate is always fixed at 15.1%, which was the official poverty rate for 2010. In other words, switching between

[18] For the CIPM the housing share is set to 0.382, which is the share of overall consumption dedicated to housing in 2010 Consumer Expenditure (CE) Survey data.

poverty measures merely changes the "ranking" of individuals, not the absolute number of individuals in poverty. Anchoring the rates precludes us from concluding that one measure yields a more deprived population because it selects a smaller and more targeted segment of the poor.

Figure 1 shows the fixed proportions of the OPM threshold used to anchor the SPM and CIPM (in both the CPS and SIPP) at 15.1%. While the proportions applied to the SPM thresholds are between 0.97 and 1.04 (depending on the survey used and whether or not the poverty measure incorporates a geographic adjustment), the proportions are approximately 1.46 for the CIPM in the CPS and 1.68-1.69 for the CIPM in the SIPP. These patterns can be explained by the CIPM using administrative data to correct for underreported survey incomes, no longer subtracting expenses from the resource measure, and adding asset flows to the resource measure in the case of the SIPP.

4. Summary Statistics

In this section, we provide descriptive evidence of how poverty rates change with a geographic adjustment by geography, race/ethnicity, and family type.

Changes in Poverty Rates by Geography

Figures 2a and 2b show how poverty rates change with a geographic adjustment (where the national poverty rate is always anchored to 15.1%) by different levels of geography. 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.[19] Figure 2a shows state-level changes in poverty rates after applying a geographic adjustment, while Figure 2b shows differences in poverty rates at the more granular CBSA (core-based statistical area) level. A CBSA is the finest level of geography that is identifiable in the public-use CPS, and it 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 the urban center). We then classify counties that do not fall within a publicly identified CBSA into one of two groups within a state: "other metropolitan" or "non-metropolitan".

Looking first at Figure 2a, we see that the states whose poverty rates increase the most with geographic adjustments are concentrated in coastal areas – namely New England, the mid-Atlantic

[19] Furthermore, geographic adjustment factors can be publicly obtained for the CPS but not for the SIPP. Following Census Bureau standards for state-level and sub-state estimates, these differences are averaged over three years of the CPS (reference years 2009 through 2011).

region, and the West Coast – that typically have high rents. Specifically, the poverty rates for Connecticut, California, Hawaii, Maryland, Massachusetts, and New Jersey each increase by 25% or more after incorporating the geographic adjustment. On the other hand, states in the Deep South, Appalachia, and the Midwest – which typically have low housing rents – see lower poverty rates after the geographic adjustment. These patterns are starkest for Arkansas, Iowa, Kentucky, Mississippi, North Dakota, South Dakota, and West Virginia, with each seeing decreases in poverty rates of at least 25% after incorporating geographic adjustments.

One might conclude from Figure 2a that state-level differences in rental costs drive much of the variation in poverty rate changes due to geographic adjustments. Yet, Figure 2b shows substantial variation even within states – specifically between urban and rural areas. For example, California sees an increase in poverty of 37% at the state level after the geographic adjustment (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 after a geographic adjustment. Conversely, while Mississippi experiences a decrease in poverty of 26% at the state level after a geographic adjustment (driven by declines in its more rural areas), the urban areas of Jackson and Hattiesburg see decreases in poverty of less than 12.5% after geographic adjustments. More generally, the CBSA-level analysis in Figure 2b shows that incorporating a geographic adjustment appears to increase poverty rates in urban clusters and decrease poverty rates in rural areas.

The top halves of Tables 2a and 2b shed further light on the changes in poverty rates by geography. These tables show poverty rates before and after incorporating a geographic adjustment (along with the differences in those poverty rates) conditional on a set of characteristics. Table 2a uses the SPM and Table 2b uses the CIPM; within each table, Columns 1-3 pertain to estimates in the CPS and Columns 4-6 pertain to estimates in the SIPP.[20] For now, we focus on estimates for individuals living in rural areas and in each of the nine Census Divisions. Focusing first on estimates using the SPM in the CPS (Table 2a), we find that the poverty rate for rural areas decreases from 14.0% to 11.4% after incorporating a geographic adjustment. This large and statistically significant decline corroborates a core pattern Figure 2b – that a geographic adjustment indicates less poverty in rural areas. We observe similar patterns using the CIPM and looking at the SIPP, with the change in rural poverty rates being even greater in the SIPP.

[20] Appendix Tables A1a and A1b show standard errors corresponding to the rates in Tables 2a and 2b, respectively.

Using the SPM in the CPS, we also find that poverty rates increase following a geographic adjustment in the New England (9.5% to 11.7%), Mid-Atlantic (13.1% to 14.4%), and Pacific (15.1% to 19.4%) Census divisions.[21] The difference in these rates is statistically significant at the 1% level for every region. Conversely, poverty rates decrease following a geographic adjustment in the East North Central (14.6% to 13.4%), West North Central (12.3% to 10.0%), South Atlantic (16.3% to 15.9%), East South Central (18.7% to 14.2%), West South Central (17.6% to 15.6%), and Mountain (15.5% to 14.9%) Census divisions. The difference in these shares is statistically significant at the 1% level for every region except South Atlantic (for which the difference is statistically significant at the 5% level). These patterns are again consistent with the patterns in Figures 2a and 2b, and they continue to largely hold when using the CIPM and looking at the SIPP.

Changes in Poverty Rates for Other Groups

Tables 1a and 1b also report poverty rates with and without a geographic adjustment by the race/ethnicity of the sharing unit head and family type. Using the SPM in the CPS (Columns 1-3 of Table 1a), we find that poverty rates increase following a geographic adjustment for Asian- or Hispanic-headed units, while the differences are statistically insignificant for white-, black-, or other race-headed units. The differences in Hispanic and Asian percentages may be driven by the substantial increases in poverty in the Pacific region, which has large Hispanic and Asian populations. We also find that poverty rates decrease among elderly and single parent families and increase among multiple parent families following a geographic adjustment, while the differences for elderly, single childless, and multiple childless units are statistically insignificant.

Turning next to estimates using the SPM in the SIPP (Columns 4-6 of Table 1a), we observe many of the same patterns – although we now see slight decreases in poverty rates for black and other race units following a geographic adjustment. Many of these patterns also persist when using the CIPM. Concentrating first on the estimates in the CPS (Columns 1-3 of Table 1b), we find that poverty rates significantly decrease for white and elderly units and increase for Asian, Hispanic, and multiple parent units following a geographic adjustment. Similarly, in the SIPP (Columns 4-6 of Table 1b), poverty rates significantly decrease for elderly and single childless units and increase for Asian and Hispanic units following a geographic adjustment.

[21] See https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf for a map of the Census divisions.

5. Methods

In this section, we describe the empirical methods used to assess whether a poverty measure with or without a geographic adjustment does a better job of identifying material well-being. We start by examining the measures of well-being analyzed and then discuss the methods used to compare well-being across poverty measures.

Measures of Material Well-Being

We analyze ten broad domains of material well-being indicators. Four domains can be examined using both the CPS and SIPP (either because they are derived from administrative data or because they are asked about in both surveys), while six domains are specific to the SIPP. We chose these outcomes *ex ante* (i.e., prior to seeing results), and they constitute a broader set of outcomes than those used in Meyer et al. (2021). The material well-being indicators in this paper also overlap with those used in Fox and Warren (2018) and Iceland, Kovach, and Creamer (2021).

Measures Available in Both Surveys (CPS and SIPP)

In both surveys, we examine permanent income, mortality, education, and health. Our measure of permanent income comes from tax records and is defined as the sum of income from tax records for 2008, 2009, 2011, and 2012. We use the PCE deflator to convert all amounts to 2010 dollars. If a person filed a Form 1040, then we use the AGI reported on this form as his/her income. If a person did not file a Form 1040, then we use the sum of incomes reported on Forms W-2 and 1099-R.[22] In our analysis, we analyze permanent income at the SPM unit level and adjust income according to the equivalence scale recommended in National Academy of Sciences (1995).[23] Next, we use the SSA's Numident file to construct two measures of mortality: having died by December 31, 2015 and having died by March 1, 2019. For each of these measures, we assess mortality at the level of both the individual and SPM unit head.

We use years of education for the SPM unit head as our education outcome in the CPS and SIPP. We compute years of education from an individual's survey-reported highest grade

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[22] 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.

[23] 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 $P = F = 0.7$.

completed.[24] Lastly, we examine self-reported health in both the CPS and the SIPP. In both surveys, we use an indicator for fair or poor health quality at both the head and individual levels. In the SIPP, we look at two other binary health indicators: having a condition that limits the kind or amount of work you can do and having a condition that prevents work.

Measures Available in SIPP Only

In the SIPP, we additionally analyze six broad domains of well-being: material hardships, home quality problems, appliances owned, assets owned, food security, and public services/safety. Our data for material hardships, home quality problems, and appliances owned come from the Wave 6 topical module. For each of these three domains, we use the same variables as in Meyer et al. (2021). For material hardships, we examine the following eight binary indicators: not meeting all essential expenses, not paying full rent, being evicted because of rent, not paying full energy bill, having energy service disrupted, having telephone service disconnected, needing to see doctor but being unable to go, needing to see dentist but being unable to go, and not having enough food. The seven binary home quality indicators that we analyze cover the presence of pests, leaking roof, broken windows, electrical problems, plumbing problems, cracks in walls, and holes in floor. The eight appliances owned we consider are microwaves, dishwashers, air conditioning, televisions, personal computers (PCs), washing machines, dryers, and cell phones.

Next, we use the topical modules for Waves 4 and 7 to define measures of assets owned. We consider five different asset measures: total assets, home equity, vehicle equity, other assets, and net worth. Total assets cover the sum of home equity, vehicle equity, and other assets. Other assets consist of interest-earning assets, stocks and bonds, IRA and KEOGH accounts, 401(k) and Thrift accounts, business equity, and SIPP's blanket variable for other assets. We then calculate net worth as total assets minus total debt (secured and unsecured).[25] We again use the Wave 6 topical module to define measures of food security. The eight binary food security indicators that we consider are: not eating sufficient food in household, not having enough to eat in house, buying food that did not last, not being able to afford balanced meals, children not eating enough, cutting size or skipping meals, eating less than you feel you should, and not eating for a whole day.

[24] In cases where an individual reports a range of values for highest grade completed, (e.g., 1st to 4th grade, 5th to 6 grade, 7th to 8th grade), we take the midpoint. We set years of education to 14 for associate's degree, 16 for bachelor's degree, 18 for master's degree, 20 for professional school degree, and 21 for doctorate degree.

[25] This differs from SIPP's definition of net worth, which consists of total assets minus total unsecured debt.

Finally, we use the Wave 6 topical module to define our public service and safety measures. The twelve binary indicators that we consider are: having inadequate public transportation, being afraid to walk alone at night, carrying anything for safety when going out, having undesirable public services, dissatisfaction with fire department, dissatisfaction with the area's hospitals, dissatisfaction with the local police, dissatisfaction with the area's public schools, dissatisfaction with the area's public services, staying at home for safety reasons, taking someone with you when going out for safety reasons, and having the threat of crime be enough that you would move.

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 material well-being on 1) indicators for poverty status with and without a geographic adjustment and 2) covariates reflecting characteristics of the sharing unit or the head of the unit. Formally, we estimate the following regression using the sample of all sharing unit heads (and, for some outcomes related to mortality and health, the sample of all individuals):

$$\textit{Well-Being} = \alpha + \beta_1 \textit{ Geographic-Only Poor} + \beta_2 \textit{ Always Poor} + \beta_3 \textit{ Never Poor} + \boldsymbol{\lambda}'\boldsymbol{X} + \varepsilon, \qquad (5)$$

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 both with and without a geographic adjustment, and *Never Poor* is an indicator for being non-poor whether or not a geographic adjustment is used. The reference group is therefore those who are poor without a geographic adjustment but not poor with a geographic adjustment (i.e., non-geographic-only poor). We compare the non-overlapping groups that are affected by geographic adjustments (i.e., those added to and removed from poverty) to clarify our analyses, as most individuals in poverty are not affected by geographic adjustments. ***X*** is a vector of characteristics of the sharing unit or its head, though we later discuss alternative estimates with a more limited set of covariates below.[26]

[26] The main set of covariates in 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.

In evaluating a geographic adjustment, we compare individuals whose poverty status changes when switching between measures with and without a geographic adjustment. In the framework of equation (5), the relevant coefficient is β_1. If β_1 is less than 0, then the geographic-only poor are more likely to be disadvantaged than the non-geographic-only poor (assuming a higher value for the dependent variable signifies greater well-being). This would imply that incorporating a geographic adjustment helps to better identify a more deprived population. For binary outcomes, we estimate equation (5) using a probit model and calculate average partial effects (APEs) over the geographic- and non-geographic-only poor subgroups.[27] For non-binary outcomes, we estimate equation (5) using a linear model. We report heteroskedastic-robust standard errors, and we 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.[28]

Shares and Counts by Geographic Poverty Category

In Table 2, we report the weighted shares of individuals and un-weighted counts of individuals and sharing units for each of our four mutually exclusive and exhaustive poverty categories in the CPS and SIPP (using the SPM and CIPM). These four categories are: those who are not poor with or without a geographic adjustment ("Never Poor"), poor without a geographic adjustment but not poor with a geographic adjustment ("Non-Geographic-Only Poor"), poor with a geographic adjustment but not poor without a geographic adjustment ("Geographic-Only Poor"), and poor with and without a geographic adjustment ("Always Poor").[29]

Starting first with the SPM, Column 1 shows that 83.38% of population-weighted individuals in the CPS are never poor, 13.58% of individuals are always poor, and 1.52% of individuals each are non-geographic-only and geographic-only poor. The most important groups for our analysis are the non-geographic-only and geographic-only poor, as these "switcher" groups

[27] It is crucial to calculate APEs over only the part of the overall sample that provides the relevant identifying variation. Otherwise, calculating APEs over the entire sample (i.e., including the always and never poor subgroups) may lead to unrepresentative estimates of APEs from the probit models.
[28] For regressions at the individual level with mortality or health outcomes, we use individual survey weights.
[29] Using these disjoint poverty categories, Appendix Tables A2a (for the SPM) and A2b (for the CIPM) provide another perspective on how the demographics of the poor change when applying a geographic adjustment. These tables show the conditional percentages of individuals in each of the four geographic poverty categories by characteristic. The results echo those found in Tables 2a and 2b. Appendix Tables A3a and A3b show p-values corresponding to t-tests of estimates for the geographic-only poor, "Always Poor", "Never Poor", and "All" groups against the non-geographic-only poor.

are what our regressions rely upon for identification. By construction, the weighted shares for these two groups are the same since poverty rates with and without geographic adjustments are always anchored to 15.1%. For the SPM in the SIPP, Column 4 shows that each of these "switcher" groups constitute 1.83% of the population. For the CIPM, the non-geographic-only and geographic-only poor each make up 1.43% and 1.46% of the populations in the CPS and SIPP, respectively. Even though poverty rates are calculated across individuals, the numbers of sharing units in Columns 3 and 6 are particularly relevant for this analysis because most of our main regressions are at the sharing unit level. However, even our smallest geography category (those who are geographic-only poor using the CIPM in the SIPP) includes 400 sharing units.

6. Main Regression Results

We now describe our main regression estimates that compare differences in a wide variety of well-being indicators between the SPM and CIPM with and without a geographic adjustment. We start by describing the results for the SPM before moving to discuss the results for the CIPM.[30]

Estimates for the SPM

Table 3a shows regression estimates of a wide range of well-being outcomes – encompassing 71 measures spanning ten domains and two surveys – on an indicator for being geographic-only SPM poor relative to being non-geographic-only SPM poor.[31] The point estimates in Column 1 correspond to β_1 in equation (5) for linear outcomes and the APEs of β_1 for binary outcomes, and Column 2 displays the heteroskedastic-robust standard errors associated with the point estimates. For every outcome, Columns 3 and 4 show the mean value for the non-geographic-only poor (i.e., the reference group against which to evaluate the regression coefficient for being geographic-only poor) and the overall mean. Finally, Column 5 displays an indicator for

[30] 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).

[31] Appendix Tables A4-A12 provide more detailed regression output containing the coefficients on the "Always Poor" and "Never Poor" categories for each of the outcomes in Table 3a. Appendix Table A22 provides even more detailed output containing the coefficients on each of the covariates for selected well-being indicators. The estimates in these appendix tables are all based on linear models (even for binary outcomes) because they are from a previous Census disclosure. However, the point estimates from a linear probability model tend to be very similar to the APEs from a probit model. Furthermore, these appendix tables do not contain the fuller estimates for models examining public services outcomes in the SIPP, as they were not disclosed in time. These estimates are available upon request.

whether the signs of the point estimates in Column 1 signify that geographic adjustments identify a more deprived population (indicated by "+") or a less deprived population (indicated by "–"). Given that most domains have multiple outcomes, we bold one summary outcome per domain and survey.

We first discuss the results for permanent income, where higher amounts signify greater well-being. We find that the geographic-only poor have higher permanent income by $28,630 in the CPS and $17,150 in the SIPP, with both differences statistically significant at the 1% level. When evaluated against the means for the non-geographic-only poor in Column (3), the geographic-only poor have approximately 100% higher permanent income in the CPS and 50% higher permanent income in the SIPP. In other words, low incomes appear less permanent in high-cost areas, which is noteworthy given the damaging effects of persistent poverty found in prior studies (see, e.g., Duncan and Rodgers 1991). Looking next at years of education for the SPM unit head (where higher values again signal greater well-being), we find that the geographic-only poor have 0.40 (3%) and 0.56 (5%) more years of education than the non-geographic-only poor in the CPS and SIPP, respectively. Both effects are again statistically significant at the 1% level.

We subsequently turn to mortality, where a higher probability is now associated with lower well-being. The geographic-only poor are associated with lower mortality rates than the non-geographic-only poor for every measure analyzed, although none of the estimates are statistically significant at conventional levels. The statistical imprecision of these estimates may stem from mortality being a relatively infrequent outcome, with the estimates associated with dying by 2015 generally being more imprecise than the estimates associated with dying by 2019. The estimates in the CPS are also slightly less noisy than those in the SIPP, as the CPS has roughly double the sample size. Indeed, the estimate associated with the SPM unit head dying by 2019 in the CPS is only marginally insignificant at the 10% level. Turning from mortality to health problems more generally, we find in the CPS that the geographic-only poor are 27% and 17% less likely than the non-geographic-only poor to have poor or fair health quality at the individual and head levels, respectively. In the SIPP, the geographic-only poor are 39% and 47% less likely to have poor or fair health quality at the individual and head levels (respectively), 54% less likely to have a health condition that limits work, and 59% less likely to have a health condition that prevents work. All of these effects are statistically significant at the 1% level.

We next examine eight different material hardships in the SIPP as well as a summary measure of the total number of hardships (with more hardships being associated with lower well-being). The geographic-only poor have 0.16 (13%) fewer total hardships than the non-geographic-only poor, but this estimate is statistically insignificant. Out of the eight individual hardship measures, seven are associated with lower deprivation after geographic adjustments. However, none of the estimates for the individual hardship outcomes are statistically significant. We also examine seven different home quality problems in the SIPP along with a summary measure of the total number of home quality problems (with more home quality problems being associated with lower well-being). The geographic-only poor have 0.12 (33%) fewer total home quality problems than the non-geographic-only poor, with this estimate being statistically significant at the 10% level. Four out of the seven individual problems are associated with lower deprivation after geographic adjustments (with the estimates for leaking roof, broken windows, and holes in floor being statistically significant at the 10% level), while the three individual problems that suggest greater deprivation have statistically insignificant estimates.

We now turn to analyzing the ownership of eight different appliances in the SIPP and a summary measure of the total number of appliances (with more appliances being associated with greater well-being). The geographic-only poor have 0.19 (3%) fewer total appliances than the non-geographic-only poor. While this estimate is small and statistically imprecise, it is also the only summary measure estimate to suggest that geographic adjustments may identify a more deprived population in poverty. Breaking down the results by individual appliances shows that the geographic-only poor have greater ownership of four appliances (with ownership of computer and cell phone statistically significant at the 1% level) and lower ownership of four other appliances (with ownership of air conditioning, washer, and dryer statistically significant at the 1% level).

However, the differences in ownership of air conditioning and washers/dryers may in part reflect the characteristics of the locations in which the groups reside. Specifically, the geographic-only poor tend to be located in California and the Northeast while the non-geographic-only poor tend to be located in the Deep South; the former regions are likely to be cooler (indicating less of a need for air conditioning) and denser (leading to fewer in-unit washers and dryers) than the latter. These hypotheses are supported by the results in Appendix Table A24, which show the coefficient estimates on being geographic-only poor (from regressions of each of the appliance outcomes) after controlling for average monthly temperatures at the county level and the proportion of single-family homes by county. After including these covariates, we find that the geographic-only poor have (statistically insignificantly) more total appliances than the non-geographic-only poor, with the estimates for air conditioning and dryer now statistically insignificant.

We next examine the ownership of assets (with higher amounts associated with greater well-being) and find that the geographic-only poor have $96,560 (116%) more total assets than the non-geographic-only poor, with this difference statistically significant at the 1% level. However, the difference in net worth is not statistically significant, as the geographic-only poor also have significantly higher amounts of total debt than the non-geographic-only poor. It is worth noting that positive levels of debt may not necessarily reflect increased disadvantage, as debt indicates the ability to borrow and enables one to consume. Breaking down the estimate for total wealth by its components, we find that the geographic-only poor have $31,920 (79%) more in home equity, $1,279 (34%) more in vehicle equity, and $63,370 (163%) more in other assets (which include checking and savings accounts, retirement accounts, stocks and bonds, etc.). The estimates for home and vehicle equity are statistically significant at the 1% level, while the estimate for other assets is not statistically different from zero.[32]

We also analyze the presence of seven different food security problems in the SIPP and a summary measure of the total number of food security problems (with more food security problems being associated with lower well-being). The geographic-only poor have 0.18 (17%) fewer total food security problems than the non-geographic-only poor, although this estimate is statistically insignificant. Six out of the seven individual food security problems are associated with lower deprivation after a geographic adjustment, although only the estimates corresponding to not having enough food to eat and not being able to afford balanced meals are statistically significant at conventional levels.

For the final domain of outcomes, we examine the presence of twelve public services/safety problems in the SIPP and a summary measure of the total number of problems (with more public services problems being associated with lower well-being). The geographic-only poor have 0.03 (3%) fewer public services/safety problems than the non-geographic-only poor, although this estimate is statistically insignificant. Out of the twelve individual public services problems, seven

[32] Note that it is not the case that unconditional home values are mechanically correlated with median rents – while home values are likely positively correlated with median rents conditional on owning a home, home ownership itself is likely negatively correlated with median rents.

are associated with lower deprivation after geographic adjustments (having inadequate public transportation and being unsatisfied with the police are statistically significant at the 1% and 5% level, respectively). Of the five measures that are associated with higher deprivation after geographic adjustments, two are statistically significant (having stayed at home for safety and having taken someone with you for safety reasons) at conventional levels.

In summary, we find strong evidence that incorporating a geographic adjustment to SPM poverty thresholds identifies a less deprived poor population than those who are otherwise poor without a geographic adjustment. For 55 of the 71 total well-being indicators and 13 of the 14 summary measures that we analyze, we find that the geographic-only poor appear to be less deprived than the non-geographic-only poor (with estimates being statistically significant for 24 individual outcomes and 8 summary measures).[33] A caveat of these results, however, is that the SPM may classify some individuals with high levels of well-being as being in poverty, as it relies on survey-reported incomes that are subject to underreporting and does not explicitly account for the flow value of assets.[34] Partly as a result of these issues, we also examine results using an alternative poverty measure (the CIPM) that corrects for misreporting using administrative data and explicitly incorporates the income flow from assets.

Estimates for the Comprehensive Income Poverty Measure

Table 3b presents the analog to the estimates in Table 3a using the CIPM.[35] Once again, our results broadly show that a geographic adjustment appears to identify a less deprived population in poverty. The geographic-only poor have $24,140 (99%) and $17,800 (72%) more permanent income in the CPS and SIPP, respectively, and 0.57 (5%) and 0.70 (6%) more years of education in the CPS and SIPP than the non-geographic-only poor. Each of these estimates is statistically significant at the 5% level. The geographic-only poor also have lower rates of mortality than the non-geographic-only poor for five of the eight mortality measures analyzed; for one of

[33] Note that many of the statistics within a given survey (e.g., SIPP) are not independent if the outcomes are correlated, while statistics are independent across surveys even if they correspond to a similar outcome.

[34] As an implication of this caveat, we find that those who are poor both with and without a geographic adjustment ("Always Poor") have lower levels of deprivation than the non-geographic-only poor across a number of domains, including permanent income (Appendix Table A4), years of education (Appendix Table A5), health problems (Appendix Table A7), total wealth (Appendix Table A11), and food security problems (Appendix Table A12).

[35] Appendix Tables A13 through A21 cover more detailed regression output containing the coefficients on the "Always Poor" and "Never Poor" categories, and Appendix Table A23 covers even more detailed output containing the coefficients on each of the covariates for selected well-being indicators.

these measures (death by 2019 in the CPS for the unit head), our estimate is statistically significant at the 5% level. In contrast, the estimates for the three measures (death by 2015 for both the individual and unit head as well as death by 2019 for the unit head, all in the SIPP) that point to higher rates of mortality among the geographic-only poor are statistically insignificant. Turning to health problems more generally in the SIPP, the geographic-only poor are 21% and 31% less likely to have poor or fair health quality at the individual and head level (respectively), 21% less likely to have a health condition that limits work, and 18% less likely to have a health condition that prevents work than the non-geographic-only poor. The health estimates are of the same sign and slightly larger magnitudes in the CPS, with each statistically significant at conventional levels.

The geographic-only poor also have 0.18 (14%) fewer total material hardships than the non-geographic-only poor, with all eight individual hardship measures associated with lower deprivation after a geographic adjustment. However, none of these hardship estimates are statistically significant. Additionally, the geographic-only poor have 0.16 (38%) fewer total home quality problems than the non-geographic-only poor, with this estimate being statistically significant at the 5% level. Six of the seven individual home quality problems are associated with lower deprivation after a geographic adjustment, with only the estimates for pests, leaking roof, and holes in the floor being statistically significant at conventional levels. The geographic-only poor have 0.23 (4%) fewer total appliances than the non-geographic-only poor, but this summary estimate is statistically insignificant and stems from the lower ownership of air conditioning units, washers, and dryers outweighing the higher ownership of dishwashers, computers, and cell phones among the geographic-only poor. Yet, after controlling for average monthly temperatures and the proportion of single-family homes by county, we again find that the geographic-only poor have more total appliances and higher ownership of air conditioning units than the non-geographic-only poor (although both estimates are statistically insignificant).

Using the CIPM, we also find that the geographic-only poor have \$61,530 (211%) more total wealth and \$26,070 (384%) more net worth than the non-geographic-only poor, although the estimate for net worth is again statistically insignificant. Breaking down by the components of total wealth, we find that the geographic-only poor have substantially higher amounts for non-home or vehicle assets. Next, the geographic-only poor have 0.211 (22%) fewer total food security problems than the non-geographic-only poor, with this estimate being statistically significant at the 10% level. Six of the seven individual food security problems are associated with lower deprivation after geographic adjustments, although the only statistically significant estimates are those corresponding to cutting/skipping meals and eating less than one should. Finally, the geographic-only poor have 0.069 (5%) fewer public services problems than the non-geographic-only poor, although this estimate is statistically insignificant. Six of the eleven individual public services problems are associated with lower deprivation after geographic adjustments, although only the estimate for inadequate public transportation is statistically significant.

Putting these results together, we again find that incorporating a geographic adjustment to poverty thresholds – this time using the CIPM – continues to identify a less deprived poor population than those who are otherwise poor without geographic adjustments. This result holds for 55 of the 70 total well-being indicators and 12 of the 14 summary outcomes that we analyze, with estimates being statistically significant for 24 individual outcomes and 10 summary measures.

7. Extensions and Robustness Checks

In this section, we discuss a series of extensions and robustness checks to our main results. We begin by showing the effects of scaling the geographic adjustment factor. We then show results using Regional Price Parities as an alternative price index. Using the original Median Rent Index, we also show the effects of geographic adjustments on the material well-being of those at other income cutoffs corresponding to deep and near poverty. Furthermore, we calculate estimates based upon the Official Poverty Measure (OPM). Finally, we discuss analyses that control for a more parsimonious set of covariates as well as for either rural status or geographic region. We focus on the CIPM for these additional analyses, although results using the SPM point in the same direction.

Scaling the Geographic Adjustment Factor

We first examine the effects of scaling the geographic adjustment factor by fractions from 0.1 to 1, where 0 corresponds to no adjustment and 1 corresponds to the full geographic adjustment underlying our main results. 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 geographic adjustment factor to account for amenities, we explore a range of weights. Renwick (2018) provides the closest analog to our analysis, although she only uses a scaling of 0.5 to reduce the geographic adjustment.

More formally, recall that the original geographic adjustment factor for the SPM threshold in equation (4) can be written as follows:

$$\textit{Adjustment Factor}_{t,sm} = (\textit{Housing Share}_t \times \textit{MRI}_{sm}) + (1 - \textit{Housing Share}_t), \tag{6}$$

where t is the unit's housing tenure and s and m denote the unit's state and MSA, respectively. The scaled adjustment factor for the SPM threshold can be written as:

$$\begin{aligned}\textit{Scaled Adjustment Factor}_{t,sm} &= \textit{Fraction} \times (\textit{Housing Share}_t \times \textit{MRI}_{sm}) \\ &\quad + (1 - \textit{Fraction} \times \textit{Housing Share}_t),\end{aligned}$$

where *Fraction* ranges from 0.1 to 1 (in tenths).[36] In other words, we simply scale the full geographic adjustment factor towards 1. For example, suppose the full adjustment factors are 1.5 and 0.6 for two different observations. Applying a 0.5 scale factor changes the adjustment factors to1.25 and 0.8. We then multiply these scaled geographic adjustment factors by the base threshold and equivalence scale to obtain revised poverty thresholds corresponding to different scalings of the geographic adjustment. We continue to always anchor poverty rates at 15.1%. An implication of a lower fraction is that fewer observations will switch in or out of poverty as a result of applying a geographic adjustment. We therefore focus on permanent income and years of education in these analyses, as these outcomes – in addition to being available in both the CPS and SIPP – have substantial variation and thus allow for greater statistical power.

Figures 3a and 3b show regression estimates of permanent income and years of education – focusing on the coefficient for being geographic-only CIPM poor – when varying the fraction of the MRI variation applied to the CIPM poverty threshold.[37] For each outcome, the solid circles reflect point estimates from the CPS and the hollow triangles reflect point estimates from the SIPP (surrounded by 95% confidence bands). Note that the confidence bands are wider (i.e., standard

[36] For the CIPM, the housing share of expenditures no longer varies by housing tenure.
[37] Appendix Figures A2a and A2b show the analogs of these figures using the SPM (with the full regression outputs in Appendix Tables A25-A28). For the CIPM, Appendix Tables A29-A32 display the full regression outputs.

errors are larger) at lower fractions, where fewer observations are classified as geographic-only and non-geographic-only poor. A key result in these figures is that the point estimates for permanent income and education in both surveys are always positive across the entire distribution of scaling factors – with the exception of the statistically insignificant estimate for years of education in the CPS after applying 10% of the geographic adjustment. This result suggests that even a partial adjustment for geographic differences in rental costs is likely to identify a poor population that is less deprived. The point estimates are in a fairly tight range for fractions between 0.5 and 1.0 – for permanent income, the coefficients on being geographic-only poor range from \$24,140 to \$28,330 in the CPS and from \$14,600 to \$18,420 in the SIPP; for years of education, the coefficients range from 0.52 to 0.732 in the CPS and from 0.538 to 0.698 in the SIPP.

Using Regional Price Parities Rather Than the MRI Price Index

We next assess whether a geographic adjustment to poverty thresholds continues to identify a less deprived poor population if we use an alternative geographic price index. In place of the MRI, we use Regional Price Parities (RPPs) that reflect the variation in prices across a broad set of goods covering housing, transportation, food, education, recreation, medical, apparel, and other items.[38] We obtain RPP values from the BEA for calendar year 2010 by metropolitan area and – for areas that do not fall into a specified metropolitan area – for all other metropolitan areas and non-metropolitan areas within a state. We assign the correct RPP to each individual based on their survey-identified place of living, first matching on specific metropolitan area before matching on state/metropolitan status. The RPPs are defined such that the national average is 1, so the RPP-adjusted poverty threshold is the base threshold multiplied by the equivalence scale and the RPP. In other words, we compute and anchor poverty in the same way as for the MRI, except we do not need to multiply by an expenditure share since the RPPs are the full geographic adjustment factors. Panel A of Table 4 shows the weighted shares and un-weighted counts of observations falling into each of the geographic CIPM categories defined using the RPP adjustment.[39] The shares of

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[38] 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 Figures A1a and A1b). 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.

[39] Panel A of Appendix Table A33 shows the analogous numbers using the SPM.

individuals in each of the "switcher" groups for the CIPM under the RPP adjustment (1.45% in the CPS and 1.51% in the SIPP) are comparable to the corresponding shares under the MRI adjustment (1.43% in the CPS and 1.46% in the SIPP).

Table 5 shows regression estimates of selected well-being indicators on CIPM poverty categories using the RPP adjustment, focusing on the coefficient for being geographic-only poor.[40] We examine fourteen summary outcomes, encompassing ten unique measures (one from each domain of outcomes for each survey). Four of these measures are available in both the CPS and SIPP, and six of these measures are available only in the SIPP. For thirteen of the fourteen measures, the sign of the regression coefficient suggests that incorporating a geographic RPP adjustment identifies a less deprived population (with ten of these estimates statistically significant at the 10% level). The only well-being indicator for which the RPP adjustment identifies a more deprived population is the number of appliances, but – as previously discussed – this effect is likely driven in part by the location-specific needs of the non-geographic-only poor.

The estimates in Table 5 are comparable to their counterparts using the MRI in Table 3b, although the estimates for the numbers of hardships and appliances are statistically significant under the RPP adjustment (but not the MRI adjustment) while the estimate for the number of home quality problems is statistically significant under the MRI adjustment (but not the RPP adjustment). In sum, these results show that adjusting for price differences across a broader bundle of goods (beyond housing) does not change our central finding that a geographic adjustment to poverty identifies a less deprived poor population. Furthermore, the consistency of the results using the RPP and MRI adjustments suggests that using an intermediate geographic adjustment index like the Food, Apparel, and Rent RPP (which covers a set of goods strictly between those covered in the MRI and RPP) is likely to yield similar results.

Deep and Near Poverty

In another set of analyses, we examine the effects of a geographic adjustment to poverty thresholds (using the MRI) on the deprivation of those classified as deep poor and near poor. Deep poverty is defined as having incomes below 50% of the poverty line, while near poverty is defined as having incomes below 150% of the poverty line. To calculate deep and near poverty with and

[40] Appendix Table A34 shows the analog of this table using the SPM (with more detailed results in Appendix Table A35). For the CIPM, Appendix Table A36 shows more detailed results corresponding to these regressions.

without a geographic adjustment, we follow the same methodology as that used 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 reference year 2010. Panels B and C of Table 4 show the weighted shares and un-weighted counts of observations falling into each of the geographic deep and near poverty categories.[41] The shares of individuals in each of the "switcher" groups for deep poverty range between 0.64% and 0.66% for the CIPM, depending on the survey analyzed. On the other hand, the shares of individuals in each of the "switcher" groups for near poverty range between 1.84% and 2.10% for the CIPM.

Table 6 presents regression estimates of selected well-being indicators – the same ones as those analyzed in Table 5 – on deep and near poverty categories under the CIPM, focusing on the coefficient for being geographic-only poor.[42] Examining first the deep poverty estimates in Panel A, we find that a geographic adjustment identifies a less deprived population in deep poverty for thirteen out of the fourteen outcomes (with the estimates being statistically significant at the 10% level for seven outcomes). Moreover, the only outcome (i.e., material hardships) for which the geographic-only poor appear more deprived is associated with a statistically insignificant estimate. The point estimates for mortality are particularly notable, with the geographic-only deep poor being 40% and 50% (in the CPS and SIPP, respectively) *less* likely to have a head die by 2019 than the non-geographic-only deep poor. The estimates are so striking potentially because mortality is a tail event and the non-geographic-only deep poor (particularly those living in the Deep South) may be especially prone to suffer from health issues resulting in higher mortality.

Moving onto the near poverty estimates in Panel B of Table 7, we find that a geographic adjustment identifies a less deprived population in near poverty for eleven of the fourteen outcomes (with the estimates being statistically significant at the 10% level for five of the eleven outcomes). As a result, the findings in Table 7 strongly and consistently show that a geographic adjustment to poverty thresholds continues to identify a less deprived population even after extending our analyses to other cutoffs.

[41] Panels B and C of Appendix Table A33 shows the analogous numbers using the SPM.
[42] Appendix Table A37 shows the analog of this table using the SPM (with more extensive outputs in Appendix Tables A38 and A40). For the CIPM, Appendix Tables A39 and A41 show more extensive regression outputs.

Additional Analyses

In this final subsection, we describe a series of additional extensions and robustness checks. We start by examining the effects of geographic adjustments on the well-being of those classified as poor under the Official Poverty Measure (OPM) as an alternative to the SPM or CIPM. Although the OPM has many well-known limitations, it is also the poverty measure that is conceptually most similar to what various government programs (e.g., SNAP, Head Start, etc.) use to determine benefit eligibility.[43] Using the OPM, we find that geographic adjustments identify a less deprived population for twelve of the fourteen summary well-being outcomes (although the estimates for only five of these twelve outcomes are statistically significant at the 10% level). Moreover, the estimates for the two summary outcomes (number of appliances and number of public services problems) that point in the opposite direction are statistically insignificant. Looking at the broader set of well-being indicators, Appendix Table A42 shows that the geographic-only poor under the OPM are less deprived than the non-geographic-only poor for 49 out of 71 well-being indicators (with estimates being statistically significant for 16 outcomes).

Figure 4 summarizes the results of additional analyses that use the CIPM to examine the sensitivity of our results to the covariates used in our regression specifications.[44] First, we re-estimate our regressions using the most parsimonious set of covariates possible.[45] Upon doing so, our results continue to indicate that geographic adjustments identify a less deprived population in poverty for nine of the fourteen summary outcomes when controlling for as few demographics as possible (with five of these estimates statistically significant at the 10% level). Appendix Table A44 shows for the broader set of well-being indicators that the geographic-only poor are less deprived than the non-geographic-only poor for 39 out of 60 well-being indicators, with 14 of

[43] 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 in equation (5).

[44] Specifically, Figure 4 shows for a given model the number of outcomes (out of the fourteen outcomes examined in Tables 5 and 6) that support or do not support a geographic adjustment. Outcomes that support (do not support) geographic adjustments are tabulated to the left (right) of zero, with different color shadings to distinguish outcomes that are statistically significant at the 10% level from outcomes that are statistically insignificant. Appendix Figure A4 shows the analog of this figure using the SPM.

[45] 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.

these estimates being statistically significant.[46] Years of education is a key domain for which geographic adjustments no longer identify a significantly less deprived population after reducing the number of covariates. 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 analyze how our regression estimates change when adding either binary variables for geographic region (Northeast, Midwest, South, West) or a binary variable for rural status to our main set of controls. Our results barely budge after controlling for geographic region. Specifically, after controlling for geographic region, we find that geographic adjustments continue to identify a less deprived population in poverty for twelve of the fourteen summary outcomes, with nine of these estimates statistically significant at the 10% level.[47] In contrast, our results weaken after controlling for rural status. After doing so, we find that geographic adjustments continue to identify a less deprived population in poverty for eleven summary outcomes, with five of these estimates statistically significant at the 10% level.[48] In summary, the urban versus rural distinction between the geographic-only and non-geographic-only poor appears to be a key driver of the results we observe, whereas our results remain largely unchanged whether we examine differences across geographic regions or within geographic regions.

8. Empirical Explanations for Results

In this section, we provide some empirical explanations for the overarching result that those who are poor in higher-cost areas appear to be less deprived than those who are poor in lower-cost areas. Intuitively, this result must arise out of the idea that higher prices in certain areas are correlated with greater provision of other things valued by the poor in those areas. We test this hypothesis by calculating the correlation of local hourly wages, non-labor income, and spending on various types of amenities with local prices. While these analyses are only meant to be

[46] We examine a strictly smaller set of well-being outcomes using the CIPM because of Census disclosure concerns pertaining to small cell sizes for certain outcomes. Appendix Table A43 shows the analog of this table using the SPM.
[47] Appendix Table A46 shows for the broader set of well-being indicators that, after controlling for geographic region, the geographic-only poor are less deprived for 46 out of 60 well-being indicators, with 24 of these estimates being statistically significant). Again, we do not examine all well-being outcomes because of Census disclosure concerns relating to small cell sizes for certain outcomes. Appendix Table A45 shows the analog of this table using the SPM.
[48] Appendix Table A48 shows for the broader set of well-being indicators that, after controlling for rural status, the geographic-only poor are less deprived for 41 out of 60 well-being indicators, with 11 of these estimates being statistically significant. Appendix Table A47 shows the analog of this table using the SPM.

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

We first examine the elasticities of local hourly wages and non-labor income with respect to two price indices. Table 7a shows the coefficients from CBSA-level regressions of the natural log of various income sources on the natural log of local prices calculated using either the MRI or RPP.[49] First, 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, respectively, with both elasticities statistically significant at the 1% level. Turning to non-labor income, Social Security retirement income (per individual aged 62 and older) also increases by 0.30% and 0.40% given a 1% increase in the MRI and RPP, respectively, while Social Security disability income (per capita) actually decreases by 2.17% and 2.15% given a 1% increase in the MRI and RPP, respectively. Like Social Security retirement income, private pensions (per individual aged 60 and older) are positively correlated with prices, but the elasticities are above unity and larger (ranging from 1.37 to 1.38). We further find a significantly positive correlation between housing assistance (per capita) and prices, with housing assistance increasing by 3.6% and 3.3% given a 1% increase in the MRI and RPP, respectively. The fact that these elasticities are much higher than one suggests that the relationship between housing assistance and median rents is not likely to be purely mechanical. There are also transfers (SNAP and SSI) whose per-capita amounts are negatively correlated with prices, although only the elasticities for SNAP are statistically significant.

In Table 7b, we examine the elasticities of various categories of state and local spending (per capita) with respect to the MRI or RPP.[50] Many of these categories (e.g., spending on education, police, environment, etc.) can be interpreted as spending on amenities. For the majority of spending categories (including welfare, K-12 education, police, environment and housing, and other spending), the elasticities of spending with respect to the MRI and RPP are significantly positive and above unity. Conversely, the elasticities of higher education and health/hospital spending with respect to prices are negative (albeit statistically insignificant). Thus, the elasticity

[49] 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).

[50] Specifically, Table 7b shows coefficients from state-level regressions of the natural log of various spending amounts on the natural 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 et al. 2016). As a result, we correspondingly use MRI and RPP values calculated for calendar year 2012. The MRI values in Table 7b are scaled similarly as those in Table 7a to make the MRI and RPP elasticities comparable.

of overall education spending (which combines K-12 and higher education spending) is still significantly positive but below unity. Taken together, the results in Tables 7a and 7b indicate that hourly 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 to each other, and the elasticities in many cases are above one. These results help to rationalize the finding that geographic adjustments for local price differences lead to the identification of a less deprived poor population, as places with higher prices also have higher incomes and more amenities.

We also show in Table 7c that various 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 include household and individual incomes at age 35 (for those born between 1978 and 1983) conditional on parental income being at the 25th percentile.[51] For all geographic units of analysis, we find that household- and individual-level mobility outcomes have a strong positive association with median rent levels. These results provide further evidence that the characteristics associated with higher-price areas – such as higher incomes and greater amenities – are likely to lead to a population that is more well-off.

9. Conclusions

In this paper, we assess the desirability of a geographic adjustment to poverty measures by examining whether or not it identifies a more deprived population. For nine of the ten domains of well-being indicators that we consider, the majority of outcomes suggest that those classified as poor with a geographic adjustment (many of whom live in urban areas) are less deprived than those classified as poor without a geographic adjustment (many of whom live in rural areas). Among eight of these nine domains, at least two measures suggest that geographic adjustments statistically significantly identify a less deprived poor population. This broad finding holds for three separate poverty measures (SPM, CIPM, and OPM) analyzed in two separate surveys (CPS and SIPP). It also holds up after a variety of extensions and robustness checks, including partial adjustments that scale the geographic adjustment factor by different weights (to crudely account for amenities), using Regional Price Parities as an alternative geographic adjustment index, analyzing deep and near poverty thresholds, and varying the covariates used in the regression specification. In short,

[51] 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.

the preponderance of evidence strongly suggests that incorporating a geographic adjustment runs counter to the central objective of a poverty measure: identifying the least advantaged population.

The results in this paper are directly relevant to efforts that seek to incorporate geographic cost-of-living differences into official poverty measures. Such efforts have been proposed by a wide variety of stakeholders and – over the past decade – have been experimentally implemented by the Census Bureau through its Supplemental Poverty Measure. Geographic adjustments to poverty thresholds would not only transform the face of poverty (by classifying fewer people as poor in lower-cost areas and more people as poor in higher-cost areas), but they would also have potentially enormous ramifications for the geographic allocation of anti-poverty funding that depends on poverty rates or an individual's poverty status. These settings range from individual eligibility for key transfer programs (such as SNAP and Medicaid) to school district eligibility for Title I funding from the federal government. Moreover, our results are relevant for analyzing broader efforts by governments and other entities to vary grants and subsidies to locations based on geographic differences in cost-of-living.

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 benefit of additional years for statistical power is limited in the SIPP, as the panel nature of the survey implies that observations are not independent over time within a panel. We also hope to use the fine geography that we have available in the surveys to bring in other indicators of well-being (such as mobility) at the Census Tract level. Finally, one of the key contributions of this paper is that it identifies and uses an extensive assortment of well-being outcomes in the survey and administrative data – building upon those used in Meyer et al. (2021) – to evaluate the suitability of modifications to a poverty measure.[52] Going forward, these well-being indicators open the door for a variety of other analyses, including validating other changes to the poverty measure (e.g., incorporating in-kind transfers and asset flows to the resource measure) and measuring the targeting of government programs.

[52] While our assortment of well-being indicators provides 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.

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Tables and Figures

Table 1a. Poverty Rates with and without Geographic Adjustments (SPM)

Characteristic	CPS Poor (No Geographic Adjustment) (1)	CPS Poor (Geographic Adjustment) (2)	(2) minus (1) (3)	SIPP Poor (No Geographic Adjustment) (4)	SIPP Poor (Geographic Adjustment) (5)	(5) minus (4) (6)
Rural	13.96	11.39	-2.56***	19.96	14.31	-5.65***
Census Division						
New England	9.54	11.69	2.14***	10.75	12.00	1.25***
Mid-Atlantic	13.10	14.38	1.28***	11.62	13.41	1.79***
East North Central	14.63	13.42	-1.21***	14.72	12.09	-2.63***
West North Central	12.33	10.03	-2.30***	13.31	10.29	-3.03***
South Atlantic	16.31	15.87	-0.44**	16.84	16.18	-0.66***
East South Central	18.71	14.22	-4.49***	21.65	17.98	-3.68***
West South Central	17.63	15.62	-2.01***	17.17	14.67	-2.50***
Mountain	15.54	14.87	-0.67***	16.04	15.07	-0.97**
Pacific	15.11	19.44	4.33***	13.93	20.17	6.25***
Race/Ethnicity of Head						
White	13.62	13.54	-0.08	13.89	13.91	0.02
Black	24.22	23.76	-0.46	21.49	20.93	-0.56*
Asian	13.05	15.47	2.42***	14.44	17.22	2.78***
Other Race	20.04	20.48	0.44	21.18	19.69	-1.49*
Hispanic	24.43	26.87	2.44***	22.49	26.40	3.92***
Unit Type						
Elderly	15.77	15.40	-0.37*	14.05	13.44	-0.61**
Single Parent	32.67	31.43	-1.24***	34.68	32.81	-1.87**
Multiple Parents	12.98	13.37	0.40***	13.05	13.55	0.50*
Single Childless	25.89	25.63	-0.25	26.97	26.85	-0.11
Multiple Childless	10.02	9.94	-0.07	10.08	10.04	-0.04
Observations	205,000	205,000	205,000	88,000	88,000	88,000

Data: 2011 CPS ASEC and 2008 SIPP Panel
Notes: This table shows the poverty rate (weighted) of individuals who have a certain characteristic alongside the difference between the poverty rates. Sample consists of all individuals in each survey, and estimates are weighted using individual survey weights. *** p<0.01, ** p<0.05, * p<0.1. Results have been approved for release by the U.S. Census Bureau, authorization number CBDRB-FY21-ERD002-002.

Table 1b. Poverty Rates with and without Geographic Adjustments (CIPM)

Characteristic	CPS			SIPP		
	Poor (No Geographic Adjustment) (1)	Poor (Geographic Adjustment) (2)	(2) minus (1) (3)	Poor (No Geographic Adjustment) (4)	Poor (Geographic Adjustment) (5)	(5) minus (4) (6)
Rural	14.41	11.83	-2.59***	18.98	14.42	-4.55***
Census Division						
New England	8.56	10.52	1.96***	9.14	11.09	1.95***
Mid-Atlantic	12.57	14.50	1.93***	12.66	13.47	0.81***
East North Central	14.30	12.92	-1.38***	15.54	13.68	-1.85***
West North Central	12.84	10.94	-1.90***	11.61	9.63	-1.98***
South Atlantic	15.76	15.60	-0.16	14.98	15.08	0.10
East South Central	20.20	14.81	-5.39***	19.77	16.00	-3.77***
West South Central	18.02	16.07	-1.94***	17.47	15.63	-1.84***
Mountain	16.43	15.71	-0.72***	16.99	16.55	-0.45
Pacific	15.18	19.07	3.89***	15.73	19.90	4.17***
Race/Ethnicity of Head						
White	13.83	13.62	-0.21**	13.60	13.42	-0.18
Black	22.59	22.99	0.40	23.66	24.25	0.59
Asian	14.01	16.52	2.51***	13.48	15.82	2.34***
Other Race	19.90	20.02	0.12	21.41	20.70	-0.70
Hispanic	24.15	26.42	2.27***	27.28	30.68	3.40***
Unit Type						
Elderly	11.98	11.40	-0.58***	10.27	9.73	-0.55**
Single Parent	37.26	36.57	-0.69*	41.19	40.91	-0.28
Multiple Parents	14.26	14.61	0.34**	14.85	15.25	0.40
Single Childless	25.66	25.58	-0.08	27.02	26.61	-0.41**
Multiple Childless	8.81	8.73	-0.08	7.44	7.25	-0.19
Observations	170,000	170,000	170,000	85,000	85,000	85,000

Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data.
Notes: This table shows the poverty rate (weighted) of individuals who have a certain characteristic alongside the difference between the poverty rates. Sample consists of individuals in PIKed sharing units (and, additionally in the CPS, no whole imputes), and estimates are weighted using individual survey weights adjusted for non-PIKing at the sharing unit level (and additionally for whole imputes in the CPS). Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results have been approved for release by the U.S. Census Bureau, authorization number CBDRB-FY21-ERD002-002.

Table 2. Shares and Counts by Geographic Poverty Category

Poverty Category	CPS Weighted Share of Individuals (1)	CPS Sample # of Individuals (2)	CPS Sample # of Sharing Units (3)	SIPP Weighted Share of Individuals (4)	SIPP Sample # of Individuals (5)	SIPP Sample # of Sharing Units (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 number of individuals (both weighted share and unweighted count) and unweighted number of sharing units in each of our four geographic poverty categories for the SPM and CIPM in both the CPS and SIPP. "Never Poor" refers to being not poor under either geographic adjustments or no geographic adjustments "Non-Geographic-Only Poor" refers to being poor under no geographic adjustments and not poor under geographic adjustments, "Geographic-Only Poor" refers to being poor under geographic adjustments and not poor under no geographic adjustments, and "Always Poor" refers to being poor under both geographic adjustments and no geographic adjustments. Poverty rates are always anchored to 15.1%, which is the official rate in the CPS. The sample for the SPM estimates consists of all observations in the surveys, and estimates are weighted using original survey weights in Columns (1) and (4). 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, and estimates are 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, and estimates are weighted using individual survey weights adjusted for non-PIKing (at the sharing unit level). Results have been approved for release by the U.S. Census Bureau, authorization number CBDRB-FY20-ERD002-020.

Table 3a. Regression Estimates of Well-Being on 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 3a. Regression Estimates of Well-Being on Geographic-Only Poor (SPM) – continued

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 linked to IRS Forms 1040/W-2/1099-R and SSA Numident

Notes: This table shows the coefficient on an indicator for being geographic-only poor (vs. non-geographic-only poor) for regressions of a wide variety of well-being indicators on indicators for being in one of three geographic SPM poverty categories (omitting the non-geographic-only poor) and a vector of covariates (for the sharing unit or its head) including age, gender, marital status, unit type, and race/ethnicity. Summary measures for each domain are bolded. Sample consists of all sharing unit heads for most outcomes, except for some of the mortality and health outcomes (which are at the individual level) and mortality and permanent income outcomes (where we restrict to PIKed units in both surveys and non-whole-imputed units in CPS). Probit APEs are reported for binary outcomes. Robust standard errors are in parentheses and are calculated using replicate weights. Results have been approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY20-ERD002-020 and CBDRB-FY2021-CES005-01.

Table 3b. Regression Estimates of Well-Being on 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 3b. Regression Estimates of Well-Being on Geographic-Only Poor (CIPM) – continued

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 shows the coefficient on an indicator for being geographic-only poor (vs. non-geographic-only poor) for regressions of a wide variety of well-being indicators on indicators for being in one of three geographic CIPM poverty categories (omitting the non-geographic-only poor) and a vector of covariates (for the sharing unit or its head) including age, gender, marital status, unit type, and race/ethnicity. Summary measures for each domain are bolded. 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. Results have been approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY20-ERD002-020 and CBDRB-FY2021-CES005-016.

Table 4. Shares and Counts by Geographic CIPM Poverty Category (Additional Analyses)

Poverty Category	CPS Weighted Share of Individuals (1)	CPS Sample # of Individuals (2)	CPS Sample # of Sharing Units (3)	SIPP Weighted Share of Individuals (4)	SIPP Sample # of Individuals (5)	SIPP Sample # of Sharing Units (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 number of individuals (both weighted share and unweighted count) and unweighted number of sharing units in each of 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 analyze deep and near poverty thresholds adjusted using the MRI. Poverty rates are always anchored to 15.1%, which is the official rate in the CPS. Rates for deep poverty (i.e., having incomes below 50% of the poverty line) are anchored to 6.7%, and rates for near poverty (i.e., having incomes 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 in the CPS consists of all individuals in sharing units where at least one member has a PIK and no member is whole imputed, and estimates are weighted using individual survey weights adjusted for non-PIKing and whole imputes (at the sharing unit level). The sample in the SIPP consists of all individuals in sharing units where at least one member has a PIK, and estimates are weighted using individual survey weights adjusted for non-PIKing (at the sharing unit level). Results have been approved for release by the U.S. Census Bureau, authorization number CBDRB-FY20-ERD002-020.

Table 5. Regression Estimates of Well-Being on Geographic-Only Poor Using RPP Adjustments (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*)	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 shows the coefficient on an indicator for being geographic-only poor (vs. non-geographic-only poor) for regressions of a wide variety of well-being indicators on indicators for being in one of three geographic CIPM poverty categories (omitting the non-geographic-only poor) and a vector of covariates (for the sharing unit or its head) 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. 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. Results have been approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY20-ERD002-020 and CBDRB-FY2021-CES005-016.

Table 6. Regression Estimates of Well-Being on Geographic-Only Deep & Near Poor (CIPM)

Well-Being Indicators	Point Estimate (1)	Standard Error (2)	Mean for Non-Geog Poor (3)	Overall Mean (4)	Supports Geog Adj? (+/-) (5)
			A. Deep Poverty		
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	–
			B. Near Poverty		
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 shows the coefficient on an indicator for being geographic-only deep/near poor (vs. non-geographic-only deep/near poor) for regressions of a wide variety of well-being indicators on indicators for being in one of three geographic CIPM deep/near poverty categories (omitting the non-geographic-only deep/near poor) and a vector of covariates (for the sharing unit or its head) including age, gender, marital status, unit type, and race/ethnicity. 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. Results have been approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY20-ERD002-020 and CBDRB-FY2021-CES005-016.

Table 7a. Elasticities of Wage and Non-Wage Income with Respect to Price Indices

Outcome	**Elasticity of Outcome With Respect to MRI (1)**	**Elasticity of Outcome With Respect to RPP (2)**
Hourly Wage (per person 18-64 with HS or less)	0.874***	1.072***
Social Security Retirement Income (per person 62+)	0.160	0.199*
Social Security Disability Income (per capita)	0.296**	0.396***
Retirement Income (per person 60+)	-2.173***	-2.151***
SNAP (per capita)	1.369***	1.381***
Housing Assistance (per capita)	-2.461***	-2.972***
SSI (per capita)	3.643***	3.304***
Observations	341	341
Unit of Analysis	CBSA	CBSA

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

Data: 2011 CPS ASEC (public-use), MRI and RPP values for 2010

Notes: This table 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. In Column (1), we use 0.618 + 0.382*MRI as the price index to make the results comparable where 0.382 is the housing share of consumption found using the Consumer Expenditure Survey (CE).

Table 7b. Elasticities of Per-Capita State Spending with Respect to Price Indices

Outcome	Elasticity of Outcome With Respect to MRI (1)	Elasticity of Outcome With Respect to RPP (2)
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: Gordon et al. (2016) for 2012 spending measures, MRI and RPP values for 2012
Notes: This table 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 et al. (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. 0.382 is the housing share of total expenditures in the Consumer Expenditure Survey (CE).

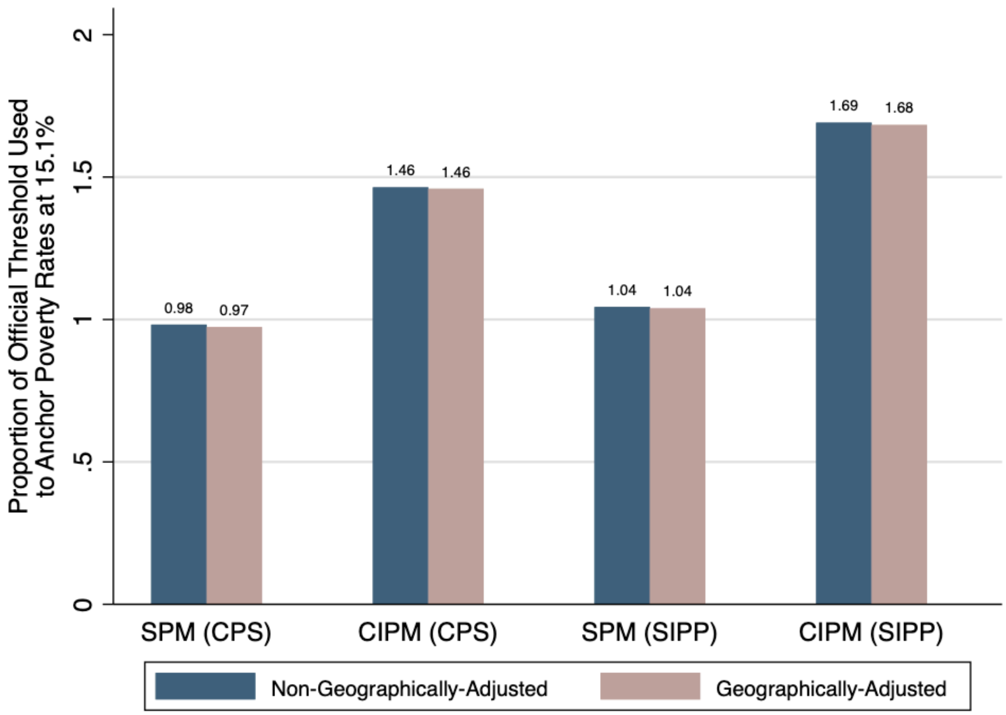
Table 7c. Regression Estimates of Mobility Outcomes on Median Rent

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

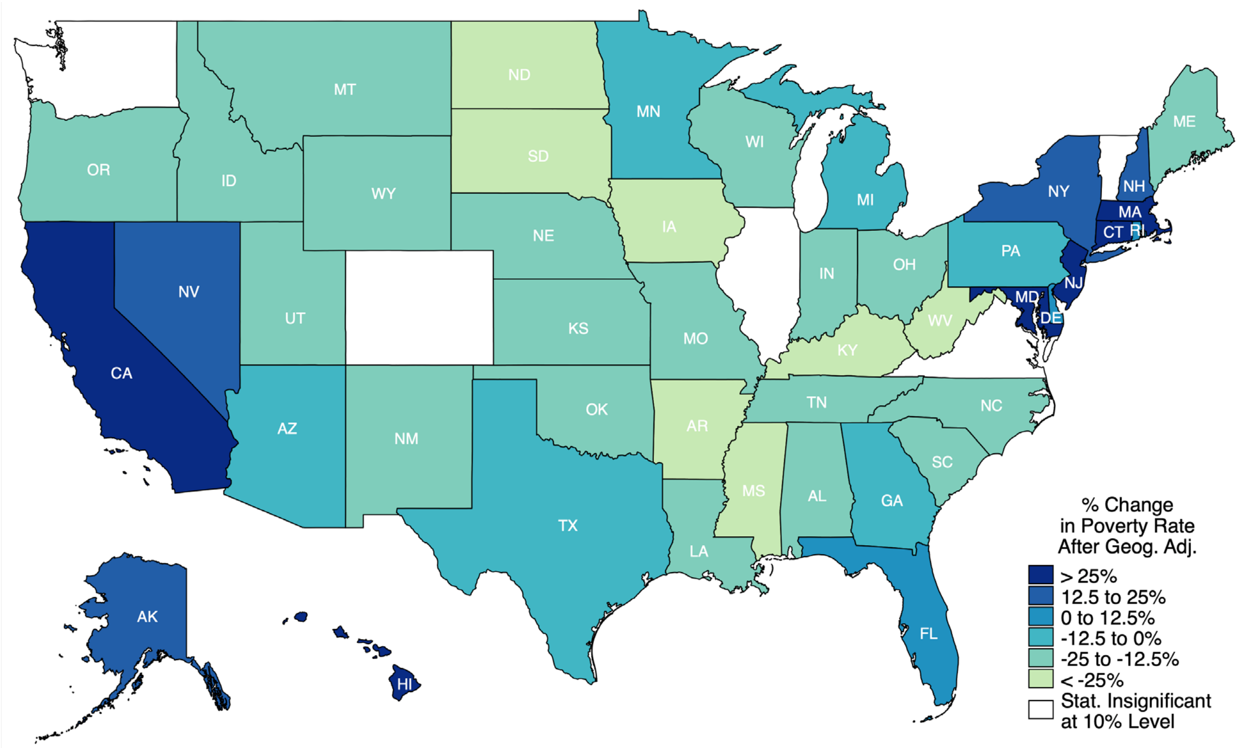
Data: Opportunity Atlas, 2009-2011 CPS ASEC
Notes: This table shows the coefficients from regressions of two mobility outcomes (household income at age 35 and individual income at age 35, each conditional on having parents in the 25th percentile of income) on median rent. The mobility outcomes are estimated 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.

Figure 1. Proportions of OPM Threshold Used to Anchor Poverty Rates at Official Levels



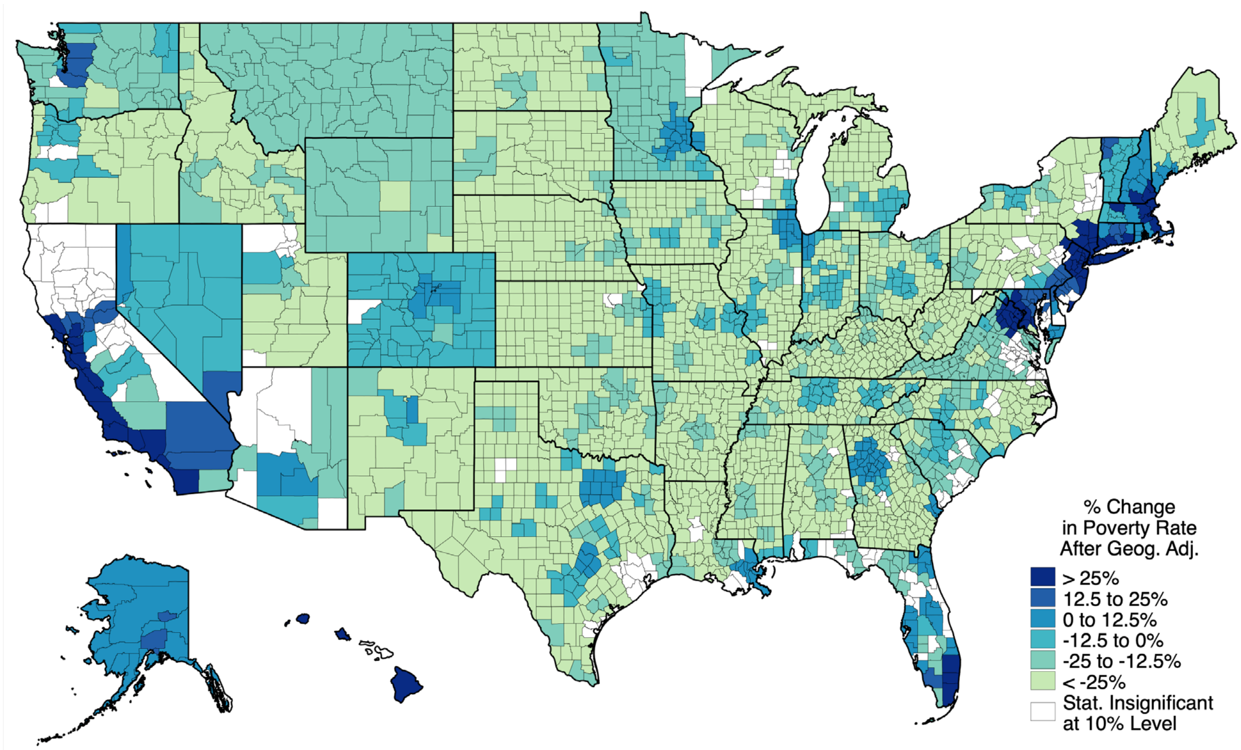
Data: 2011 CPS ASEC (public-use)
Notes: This figure shows the fixed proportions of the OPM (Official Poverty Measure) threshold used to adjust the SPM and CIPM thresholds in both the CPS and SIPP so that the poverty rates are always anchored at 15.1%, which was the official poverty rate in 2010. Results have been approved for release by the U.S. Census Bureau, authorization number CBDRB-FY21-ERD002-002.

Figure 2a. Percent Change in Poverty Rates After Geographic Adjustments (State)



Data: 2010-2012 CPS ASEC (public-use)
Notes: This map shows the difference in poverty rates by state before and after geographic adjustments (where the national poverty rates are always anchored to 15.1%). The percentage change is calculated relative to a base poverty rate without geographic adjustments. States with darker shading see increased poverty rates after adjusting for geographic differences in rental prices, states with lighter shading see decreased poverty rates, and states in white see statistically insignificant changes (at the 10% significance level) in poverty rates. Following Census Bureau standards, these state-level estimates are averaged over three years of the CPS ASEC (covering reference years 2009-2011).

Figure 2b. Percent Change in Poverty Rates After Geographic Adjustments (CBSA)



Data: 2010-2012 CPS ASEC (public-use)

Notes: This map shows the difference in poverty rates by CBSA before and after geographic adjustments (where the national poverty rates are always anchored to 15.1%). The percentage change is calculated relative to a base poverty rate without geographic adjustments. These estimates are calculated based on public-use CPS data. Rates are calculated at the CBSA level and then applied to all counties in that CBSA. For areas outside of publicly identified CBSAs, we calculate rates for two general areas within a state – "non-metro" and "other metro" – and applied to all counties in those areas. Note that we use a county-level template, even though the rates are calculated at the CBSA level and then assigned to all counties within that CBSA. If a county falls into one of the "other metropolitan" or "non-metropolitan" groups and no unit in that group is interviewed in the CPS, then that county is designated as having missing information (and shaded in white, like the counties with statistically insignificant differences in poverty rates). CBSAs with darker shading see increased poverty rates after adjusting for geographic differences in rental prices, CBSAs with lighter shading see decreased poverty rates, and CBSAs in white see statistically insignificant changes (at the 10% significance level) in poverty rates. Following Census Bureau standards, these sub-state estimates are averaged over three years of the CPS ASEC (covering reference years 2009-2011).

Figure 3a. Regression Estimates of Permanent Income by Scaling Factor (CIPM)

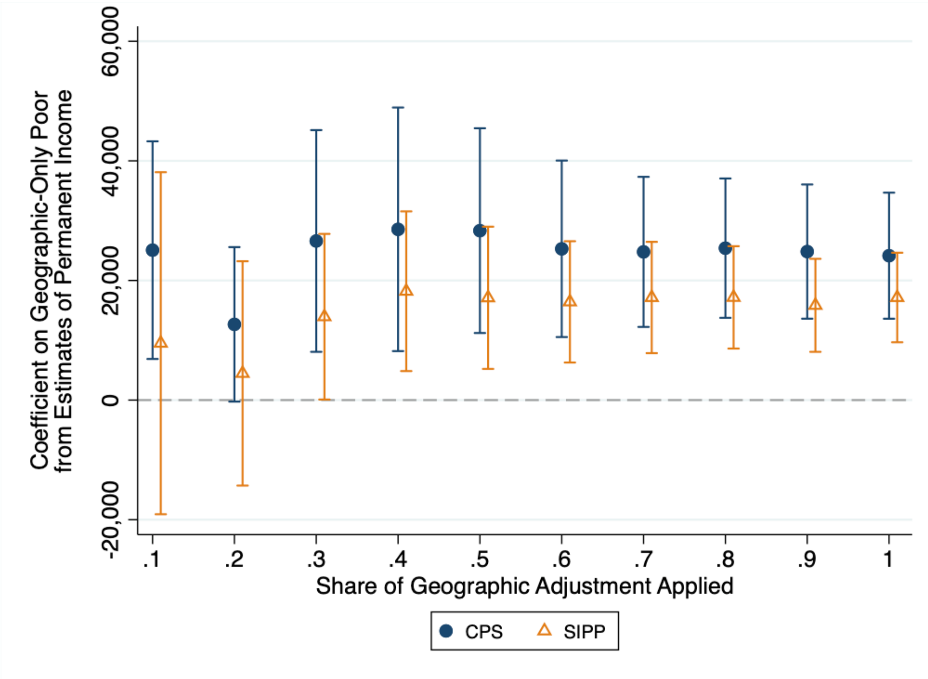
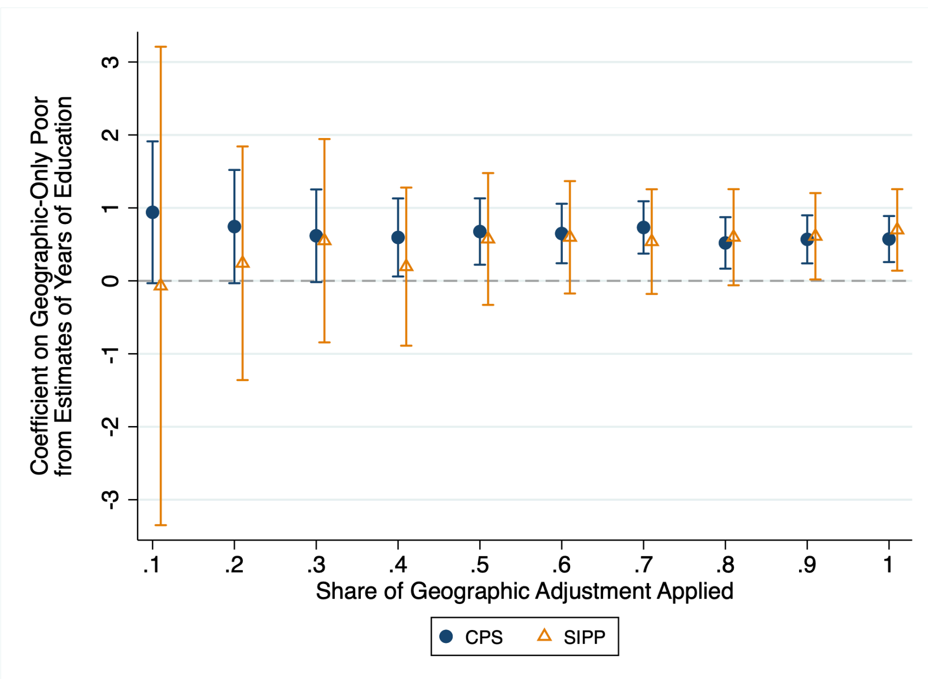
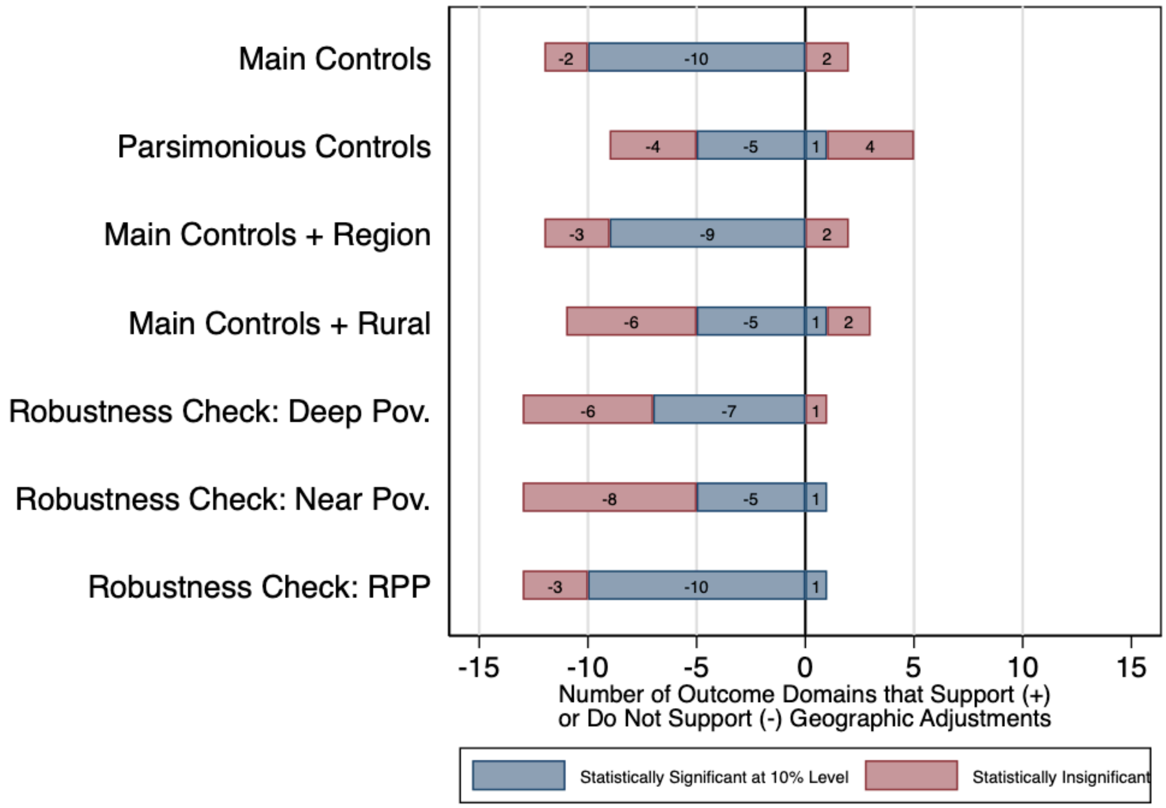


Figure 3b. Regression Estimates of Years of Education by Scaling Factor (CIPM)



Data: 2011 CPS ASEC and 2008 SIPP Panel linked to various administrative data
Notes: These figures show the coefficients on an indicator for being geographic-only CIPM poor (vs. non-geographic-only CIPM poor) for regressions of permanent income and years of education on geographic poverty categories and covariates that vary the weight placed on the geographic adjustment factor. Sample consists of all heads in PIKed sharing units (and no whole imputes in the CPS). Robust standard errors are in parentheses and are calculated using replicate weights. Confidence bands are at the 95% level. Results have been approved for release by the U.S. Census Bureau, authorization number CBDRB-FY20-ERD002-020.

Figure 4. Summary of Geographic Adjustment Effects on Well-Being by Model (CIPM)



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

Notes: This figure shows the number of summary outcomes for which a geographic adjustment identifies a more deprived population, using the CIPM. Outcomes are those in Tables 5 and 6; 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). Results have been approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY20-ERD002-020 and CBDRB-FY2021-CES005-016.