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Abstract

The U.S. Bureau of Economic Analysis has recently released regional price parities (RPPs) for the 325 Standard Metropolitan Statistical Areas and the 50 state nonmetropolitan areas. We consider the effects of RPP adjustments on four public policy issues: poverty rates, family income inequality, tax progressivity, and metropolitan-size premiums. We demonstrate that RPP adjustments strongly affect the spatial distribution of U.S. poverty, have an equalizing effect on income inequality (equivalent to a \$1,500 cash transfer to each U.S. family), and also increase effective federal tax progressivity by more than 25 percent. Income premiums for the major metropolitan areas largely disappear after adjusting for spatial prices and controlling for the characteristics of family heads. Metro-size premiums also depend on whether we adjust incomes by the overall RPPs or a narrower housing-price index (as in earlier research). We conjecture that other public policy findings are sensitive to adjustments for spatial price differences.

Keywords: regional price parities, poverty, inequality, tax progressivity, metro-size premiums.

JEL Classification: D31, H23, I32, R32.

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> "National and international statistical systems are strangely reticent on differences in price levels within countries. Nations as diverse as India and the United States publish inflation rates for different areas, but provide nothing that allows comparison across places at a point in time. The International Comparison Project, which at each round collects prices and calculates price indexes for most of the countries of the world, publishes nothing on within country differences, and in some important cases including China, Brazil, and India, rural prices are either not collected or are underrepresented…" (Deaton and Dupriez 2011, 1)

Introduction

Nobel Prize winner Angus Deaton and the prestigious National Academy Panel on Poverty and Family Assistance (Citro and Michael 1995) have called for the incorporation of spatial price adjustments in public policy analysis. Albouy (2009, 636) also points out that the U.S. federal tax code does not take into account variation in the cost of living across cities and that, "Unlike local tax differences, federal tax differences of this kind are not compensated with higher levels of local spending and may therefore affect location choices." Deaton and Dupriez (2011, 4) surmise that "the lack of these [spatial price] indexes more likely reflects the difficulty and cost of producing them" rather than a lack of usefulness for policy purposes. In the United States, these obstacles were recently overcome when the Bureau of Economic Analysis (BEA) and the U.S. Census Bureau, working with the Bureau of Labor Statistics (BLS), released the first official regional price parities (RPPs) for all U.S. metropolitan areas and state-level, nonmetropolitan areas.[1]

We investigate the effects of spatial price adjustments on four public policy issues: poverty rates, the degree of income inequality and tax progressivity, and metro-size premiums.

As Deaton and Dupriez (2011, 1) observe, "… for the same reasons that we expect price levels to be lower in poor countries—the Balassa-Samuelson theorem—we would expect prices to be lower in poorer areas within countries, at least if people are not completely mobile across space." Comparing living standards across regions in the U.S. has much in common with comparing poverty and inequality across countries in the world, but is less complicated, because in the global comparisons the wider variation in consumption patterns makes it harder to estimate relative prices. Deaton (2016, 1226) captures the dilemma,

> On the one hand, we need to compare like with like, using only goods and services that are close to identical in different countries. On the other hand, we also wish to capture what people actually spend, so that we want to use goods and services that are widely consumed and representative of actual purchases. These two requirements often stand in sharp opposition; in the extreme case where consumption bundles have nothing in common, there is no basis for comparisons of living standards.

Deaton (2010) argues that comparisons are more meaningful for broadly similar countries and, we add, still more so for regions within the same country.

For each of our policy issues (poverty, inequality, tax progressivity, and metro-size premiums), we find significant changes after adjusting for spatial price differences. The RPP adjustment has little effect on mean family money income, but has substantial effects on regional poverty rates and virtually eliminates the difference in metro and nonmetro poverty rates.[2] When we take into account the tendency for high-income families to live in high-price areas, inequality falls and effective federal tax progressivity increases by twenty-five percent. After adjusting for

RPPs and controlling for family head characteristics, the higher family incomes found in major metropolitan areas largely, but not completely, disappear.

Section 2 reviews the BEA procedures for generating the new RPP measures and describes the resulting regional price differences. Section 3 shows how RPP adjustments affect poverty, income inequality, and tax progressivity for U.S. primary families. Section 4 examines the effect of RPP adjustments on urban size premiums. Section 5 reports the main findings and suggests opportunities for future research.

Background and Data

As background for our analysis, we review some important steps leading to the appearance of the official RPP indices. *Three Budgets for an Urban Family of Four Persons* (Bureau of Labor Statistics 1979) was an early attempt by the BLS to measure regional living costs. This measure was estimated for 25 metropolitan areas and for the nonmetro areas of the four Census regions. Bishop, Formby, and Thistle (1992, 1994) used this series to study regional income convergence in the U.S. and to create regional living cost indices for 1969 and 1979. Unfortunately, the series was discontinued in the early 1980s.

Another important study, *Measuring Poverty: A New Approach* (Citro and Michael, 1995) by the National Academy Panel on Poverty and Family Assistance, raised the issue of differences in prices across regions. It proposed using housing price indices to approximate the regional price levels. As Deaton and Dupriez (2011, 4) have observed, “This proposal generated a substantial subsequent research effort within federal statistical agencies,” particularly in regard to the creation of a Supplemental Poverty Measure.[3] Among all this research, the most important piece for our purposes is Aten, Figueroa, and Martin (2011), which is the primary source for understanding the RPPs used in our analysis.

The New Regional Price Parities

This section provides an overview of the construction of the new RPP indices.[4] We then summarize the RPP data across metropolitan and nonmetropolitan areas, Census regions, and divisions using the combined BEA and CPS datasets.

Beginning in 2003-2004, the BEA estimated U.S. regional price parities for the 38 metropolitan and urban areas that the BLS uses to generate the CPI, which contained about 87 percent of the U.S. population at that time.[5] The procedure was based upon price information in the CPI (covering hundreds of consumer goods and services) and used hedonic methods to adjust for differences in product characteristics (type of outlet selling a good or service, packaging, etc.) for the 75 most important item categories, representing about 85 percent of all expenditures. For the remaining categories, a method roughly equivalent to a weighted geometric mean of prices in each item category generated relative price levels. The estimation results were then checked for outliers using methods similar to those developed for comparing relative prices across countries in the Income Comparison Project.

The BEA extended the analysis beyond areas covered by the CPI in 2005-06, using housing data from the American Community Survey (ACS). Housing is the key factor in the cost of living; rents and owners' equivalent rents are the most important consumer expenditure category by far, accounting for 30 percent of the total. Once again, hedonic regression methods allow adjustments for differences in housing characteristics (the number of rooms and bedrooms; the age and type of housing unit). For all remaining goods and services, price levels for non-CPI areas are equated to the average for that region (e.g., the Midwest). The BEA released its official real, per capita incomes for states and metropolitan statistical areas in April 2014, adjusted with RPPs, i.e., percent differences in regional average prices from the national average (Aten and Figueroa, 2014).

U.S. Price Level Differences

By construction, the national average price level is 100, and the RPPs for comparison areas are expressed as percentages of the national average. Thus, the ratio RPP/100 gives the relative price level for a comparison area. In 2012, the state metro areas with the highest RPPs were Hawaii (122.7), the District of Columbia (118.7), New York (117.5), New Jersey (114.4), and California (113.6). Arkansas (89), Alabama (89), Missouri (89.5), and West Virginia (90.1) had the lowest metro RPPs among the states. The weighted-average price level in New Jersey is about 14 percent higher (114.4/100) than the national average, and the price level in the District of Columbia is about 33 percent higher than in Arkansas or Alabama (118.7/89 = 1.334). Aten, Figeuroa, and Martin (2011) note that price levels across regions vary more for services (which account for two-thirds of total consumer expenditures) than for goods. They report that, among expenditure categories, housing rents vary the most and transportation costs (e.g., new and used vehicle purchases) vary the least. Finally, they find that lower overall price levels in rural areas are due primarily to lower housing and fuel prices.

Table 1 presents average RPP indices by metro status (plus the five SMSAs with the highest and lowest overall price levels), region, race, age, and family money income, estimated with 2012 BEA metro-level and state-level, nonmetro RPP indices and the 2013 CPS data (2012 incomes).[6] The mean RPP for primary families is slightly less than 100 (99.7). The RPP index varies by metro status (nonmetro areas are the least expensive locations with an RPP of 87.9 on average) and size (from 95.0, on average, for small metro areas to 109.3 for large metro areas). The Northeast is the highest RPP region (108.8), followed by the West (106.0). The Midwest (93.3) – not the traditionally poor South (95.5) – has the lowest population- weighted average price level among regions. The comparisons by race show that Asians live in more expensive areas (109.0) than whites (98.2), an 11 percent difference. Hispanics (103.7) also live is areas slightly more expensive than whites. RPPs vary little by the age of the family heads, but they increase with income, from 98.5 for families with incomes below $25,000 to 104.1 for families with incomes above $150,000. Families identified by the U.S. Census Bureau as “poor” face price levels (98.8) slightly below the U.S. average.

[place Table 1 about here]

U.S. Poverty and Inequality with RPP Adjustments

We begin by comparing the mean incomes, poverty rates, and Gini coefficients constructed from the CPS microdata to those published by the U.S. Census. The attempt to match the published figures gives us insight into the degree to which top-coding of incomes in the public-use CPS files influences our findings. We make the comparisons with family money income, the standard used in the published U.S. Census figures, which we construct from March 2013 CPS data. These figures provide a benchmark for assessing the effects of RPP adjustments. Census family money income includes wages and salaries, self-employment income, dividends, rent, interest, cash transfers (Social Security and Unemployment Insurance), and other cash income, but it excludes the market value of in-kind transfers, the earned income tax credit, and all taxes. In spite of its shortcomings, Census money income is the basis for the most frequently cited U.S. poverty and inequality statistics.[7]

Table 2 reports the mean family money income, the percentage of families below the poverty level (with standard errors using Bishop, Formby and Zheng 1997), and the Ginis for family money income (with standard errors using Bishop, Formby and Zheng 1998) in the U.S overall, in metro areas, and in nonmetro areas. The figures in column (1), labeled "Census," are taken from the P-60 Series, "Income and Poverty in the United States, 2013," Document FINC-01, "Selected Characteristics of Families by Total Money Income, 2012", and (for the regional poverty statistics) from the Census Bureau's "Table-Creator" website. Columns (2) and (3) in Table 2 are generated by the authors. Column (2), labeled "Microdata," presents some statistics calculated from the March 2013 Annual Demographic File, based on data for 2012 family money incomes. Column (3), labeled "RPP-Adjusted," presents statistics generated by combining the CPS microdata with the BEA's RPP adjustments for price-level differences.

From columns (1) and (2) in Table 2, we see that the summary statistics for the CPS public-use microdata match the Census figures quite closely for the U.S. overall. A comparison of columns (2) and (3) in Table 2 shows that the RPP adjustments have little effect on the overall U.S. mean income, as expected. The overall U.S. poverty rate declines slightly from 11.8 to 11.6, which we anticipated from Table 1, as poor families have RPPs less than 100 on average. The U.S. family income Gini also declines slightly from 0.450 to 0.443.[8]

Turning to the breakdowns by Standard Statistical Metropolitan Area (SMSA) status in Table 2, we can again match the mean incomes and Gini coefficients quite well (poverty rates by SMSA status are not published). Here the effect of RPP adjustments is more dramatic; the gap between the metro and non-metro incomes falls from $11,192 to $2,512. While we find that the metro poverty rate changes only slightly (11.4 to 11.6), the nonmetro poverty rate falls by a full two percentage points (13.7 to 11.7), virtually eliminating the poverty rate disparity between the metro and nonmetro regions.[9]

Regional Poverty and Inequality

Table 3 is structured like Table 2 above, where we compare our estimates of mean income, poverty, and inequality to those reported by the U.S. Census Bureau, but it focuses on the four Census regions. Our estimates for regional mean income (column 2) are very close to those published by the Census (column 1), our poverty rates are an exact match, and our Gini estimates deviate by no more than 0.002.

Adjusting for RPPs (column 3) results in both a convergence in income levels among regions and the emergence of the Midwest as the highest income region. Before RPP adjustment the mean income in the Northeast was greater than in the South by $16,925; after adjustment the gap between the highest income region (Midwest) and the South falls to $9,880.

Relative poverty rates are also affected by RPP adjustment. Before adjustment, the Northeast and Midwest have similar poverty rates (10.5 and 10.2) but after the adjustment the increase in poverty in the Northeast and the decline in poverty in the Midwest widens the gap to 2.9 percentage points. Southern poverty falls by 1.1 percentage points and Western poverty rises by 0.9. In sum, regional poverty rates largely converge with the exception of the low-poverty Midwest region.

The bottom of Table 3 reports the regional Gini coefficients. The reductions in the regional Gini coefficients are slightly smaller than the 0.008 reduction in the U.S. Gini (see

Table 2). It appears that, within each region, higher-income families live in higher-price areas. There is no change, however, in the regional inequality rankings after the RPP adjustments.

Vertical Equity, Tax Progressivity, and Regional Price Parities

The previous section showed that the effect of RPP adjustment is to reduce income inequality, which is explained by our observation that high-income families tend to live in high-price areas. Albouy (2009, 635) notes that the failure to address price differences leads to an "unequal geographical burden of federal taxation." All of this suggests that without RPP adjustments, we may understate actual federal tax progressivity.

RPP adjustments shift the distribution of income, which we designate as the pre-adjustment and post-adjustment distributions. RPP adjustments lower some family incomes (where price levels are high) and raise others (where price levels are low), creating re-rankings of households. Researchers in public finance have long recognized that the re-rankings mask some of the distributional impact of taxes and transfers and have devised methods that isolate the true vertical impact of fiscal policy changes.[10] We can adapt these methods to measure the vertical impact of RPP adjustments and compare it to those from taxes and transfers.

Lambert (1989, 182) provides a useful expression for capturing the distributional effect of the tax system, which we can apply to RPP adjustments as well. It involves comparison of the pre-adjustment (x) and post-adjustment (y) income distributions, represented here by their Gini coefficients (G_x and G_y) and the concentration index (C_y), computed from the concentration curve (the post-adjustment income vector sorted by pre-adjustment income):

$$G_x - G_y = \left(G_x - C_y\right) + (C_y - G_y). \tag{1}$$

In expression (1), we call $G_x - G_y$ the *total effect* of RPP adjustments, $G_x - C_y$ the *vertical effect*, and $C_y - G_y$ the *re-ranking correction*. Note that $C_y - G_y \leq 0$, so a naively calculated total effect would understate the vertical effect when the sign is negative. In the absence of re-rankings, $C_y = G_y$ and the correction term vanishes.[11] From Table 2 we find a total effect of $G_x - G_y = 0.4504 - 0.4428 = 0.0076$. Our calculations of the vertical effect with standard errors (Bishop, Formby and Zheng 1998) are as follows:

$$G_x - C_y = 0.4504 - 0.4395 = \underset{(0.0009)}{0.0109^*}. \tag{2}$$

Thus, the total effect of RPP adjustments, 0.0076, understates the vertical effect of RPP adjustment due to income re-rankings.

To gauge the economic importance of the RPP effect, we compare it to the vertical effect of the U.S. federal tax system. Let C_{at} be post-federal-tax family money income, then

$$G_x - C_{at} = 0.4504 - 0.4095 = \underset{(0.0004)}{0.0409^*}. \tag{3}$$

When we compare the Gini coefficient of gross family money income to the concentration index of post-federal-tax income – from CPS simulations, which include all tax credits: child care, the earned income tax credit, etc. – we find a vertical effect of 0.0409. Therefore, our RPP vertical effect is about one-quarter of the federal tax system effect (0.0109/0.0409 = 0.2665).

Next we examine the change in the vertical effect of combining both federal taxes and RPP adjustment. Let C_{aty} be post-RPP, post-tax concentration index, then

$$G_x - C_{aty} = 0.4504 - 0.3986 = \underset{(0.0005)}{0.0518^*}. \tag{4}$$

Taking into consideration the insight from Table 1, that high-income families live in high-price regions, we find that the RPP-adjusted vertical effect of federal taxes is nearly 27 percent larger (0.0518/0.0409 = 1.2665) than the vertical effect unadjusted for price levels.[12]

The tax literature also measures redistributive effects by calculating an equivalent lump-sum transfer that generates the same reduction in inequality. Deaton (2010, 10), citing Atkinson (2003), takes a similar approach to measuring the effects of revisions in purchasing power parity on global inequality. For our estimated total inequality effect (a reduction in the Gini coefficient by 0.0079), the equivalent lump-sum transfer is approximately $1,500 for each primary family in the United States, while the pure vertical effect (a reduction in the Gini coefficient by 0.0109) is equivalent to approximately $2,000. To reduce the after-tax Gini in a manner equivalent to the unadjusted tax effect would require a lump-sum transfer of $8,500. To reach the RPP-adjusted tax effect would require an additional $2,500, or $11,000 in total. Thus, we conclude that the effect of adjusting for price level changes on measured vertical equity is substantial.

Metro Size Premiums and Regional Price Parities

The theory of agglomeration economies implies that greater urban population density leads to higher productivity and that the productivity gains should be reflected in higher earnings and rents (e.g., Glaeser and Gottlieb 2009, Glaeser and Resseger 2010, Puga 2010). Glaeser and Mare (2001, 328), who use measures of spatial prices from the American Chamber of Commerce Research Association (ACCRA) despite their shortcomings, summarize the choices faced by researchers before the release of the official RPPs by the BEA:

Ideally, we would examine the difference between urban and nonurban prices more thoroughly, but standard price indices are not available for spatial comparisons. We know of no generally available set of local price indices that are more reliable than the ACCRA price indices. Housing prices are available, and they are a more reliable means of examining the urban wage premium but are only a fraction of the total budget and cannot tell us the complete picture about local price levels.

Analyses of the relationship between population density and incomes are further complicated by the possibility of omitted variable biases associated with unobserved worker productivity characteristics and city amenity or disamenity levels (e.g., Roback 1982; Combes, Gilles, and Gobillon 2008). Endogenous sorting of high-skill workers into larger cities should lead to higher real and nominal incomes there. Disamenities (congestion, pollution, crime, etc.) would have the same effect, while amenities (better access to fine dining, entertainment, and the arts) would have the opposite effect. These complications have proved difficult to sort out in the empirical literature, but the BEA's RPPs provide a more accurate and comprehensive measure of spatial price differences than was available to earlier researchers.

Before we begin our formal analysis, consider Table 4, where we compare the unconditional, unadjusted family income means by metro size (column 2) to the corresponding unconditional means adjusted by the overall RPP (column 3) and adjusted by housing prices only (column 4). To appreciate the effect of overall RPP adjustment, note that the difference in means between large and medium SMSAs drops from $11,604 to $1,618 after correcting for the overall spatial price differences. If we adjust for housing prices only, the difference between the small metro and large metro areas is more compressed: \$3659 in column (4) versus \$5940 in column (3).

We use the following OLS specification, which is patterned after equation (2) in Glaeser and Mare (2001, 328),[13] to formally test for agglomeration benefits:

$$\ln(Income)_{j,c} = (FC_j)\beta + (MS_c)\Gamma + \varepsilon_{j,c}, \quad (5)$$

where the log of money income of family *j* in geographical location *c* is a function of a vector of family characteristics, FC_j, that includes the number of children and characteristics of the family head (age, sex, race, education, and previous years of full- and part-time experience). Equation (5) also includes a vector of indicator variables, MS_c, that measures the metro size of location *c*. Specifically, equation (5) controls for metropolitan areas between 100,000 and 500,000 persons (*Small*), metro areas between 500,000 and 2.5 million persons (*Medium*), and areas with more than 2.5 million persons (*Large*). As such, the estimated vector of coefficients on metropolitan size, Γ, contains the key coefficients of interest, measuring the capitalization of agglomeration benefits into family income relative to the omitted nonmetropolitan areas.

Results for the vector of coefficients measuring metropolitan density effects from the estimation of equation (5) are presented in Table 5.[14] Column 1 of Table 5 presents results for the nominal earnings equation and indicates that families in the smallest metropolitan areas earn 8.8 percent (with a 95 percent confidence interval of 6.2 percent to 11.3 percent) more than their nonmetropolitan counterparts annually.[15] Likewise, the families living in the *Middle* and *Large* metropolitan areas earn 14.3 percent (95 percent confidence interval of 11.9 percent to 16.8 percent) and 25.0 percent (95 percent confidence interval of 22.1 percent to 27.9 percent) annual income premiums relative to nonmetropolitan families, respectively. These results imply that a nonmetropolitan family moving to the Reno, NV, Pittsburgh, PA, or Chicago, IL metropolitan statistical areas could expect an 8.8 percent, 14.3 percent, or 25.0 percent increase in family income, respectively, on average.

Our results are largely consistent with metro-size premiums that are capitalized into family money incomes. Specifically, the families in all the metropolitan areas are estimated to have significantly higher incomes than the nonmetropolitan families, and the differentials are increasing with metropolitan population density. Furthermore, formal F-tests also reject the null hypothesis of homogeneous earnings differentials across each of the pairwise metropolitan size categories at the 1% level, suggesting that the estimated income differentials by metropolitan size are significantly different from one another.

Column 2 of Table 7 presents results from a similar specification using the log of real (RPP-adjusted) family money income as the dependent variable in equation (5). Note that the impact of metropolitan location has a positive and statistically significant impact on real income across all metropolitan population density classifications. Our estimates imply that the families in *Metro 1* areas have 3.0% higher real incomes (95% confidence interval of 0.7% to 5.5%) and the families in *Metro 2* areas earn 5.9% more on average (95% confidence interval of 3.6% to 8.2%) than the nonmetropolitan families. These results are consistent with either agglomeration economies or a positive sorting equilibrium, one in which workers who have higher unobserved levels of productivity choose to live in the more densely populated areas. F-tests also reject the null hypothesis of homogenous metropolitan effects at the 5% level.

Interestingly, however, the real income premium for the largest metropolitan classification is estimated to be 3.6% (roughly two percentage points less than the *Medium* premium).[16] In terms of real income potential, a nonmetropolitan family is likely to experience the largest gains in income, on average, by moving to a medium-sized city like Pittsburgh, PA, rather than to a small city like Reno, NV, or to a large city like Chicago, IL. These results could reflect two effects – an agglomeration effect raising incomes and amenities reducing incomes – working in opposite directions, with the agglomeration effect being larger when a family moves between *Small* and *Medium* cities and smaller when it moves from *Medium* to *Large* cities. Alternatively, there could be a worker-sorting process that is nonlinear in terms of the unobserved productivity drivers.

Finally, Table 5 (column 3) allows us to compare a housing-price adjustment to the overall RPP adjustment.[17] With only a housing-price adjustment, small and large metro areas offer no income premium over the nonmetro areas. Like the overall RPP adjustment, medium-size cites provide the largest premium over the nonmetro areas, but the overall RPP premium is about twice the housing-only premium (5.7 percent vs. 2.7 percent). These findings demonstrate the importance of including a broader set of prices for goods and services when making spatial price adjustments.

Conclusion

Calls for the use of spatial price indices in public policy analysis have come from such notables as Nobel Prize winner Angus Deaton and the prestigious National Academy Panel on Poverty and Family Assistance. The U.S. government recently produced the first-ever, official regional price parities (RPPs) for all the metro and nonmetro areas in the country. Using these measures, we investigate the impact of RPP adjustments on four important public policy issues: overall and regional poverty rates, income inequality, vertical equity and tax progressivity, and urban agglomeration premiums.

We find that RPP adjustments bring regional mean incomes closer together, reduce overall headcount poverty rates slightly (poverty rates increase in the Northeast and West, but are offset by reductions in poverty rates in the South and Midwest), and most notably eliminate the metro versus nonmetro poverty rate difference. They do not alter regional income inequality rankings (higher-income families tend to live in the higher-price areas in each region); however, the adjustments affect both overall inequality and effective federal tax progressivity. Inequality, measured by the Gini coefficient, declines by an amount equivalent to a $1,500 cash transfer to each U.S. primary family. Correcting for local prices increases effective tax progressivity by more than 25 percent, or the equivalent of a $2,500 per family cash transfer.

Additionally, we use the RPPs to revisit the income premiums associated with metropolitan areas. We find that, after adjusting for RPPs and controlling for the family head's characteristics, the higher family incomes found in major metropolitan areas largely, though not completely, disappear.

Table 1
Average Regional Price Parities for Selected Groups, 2012

Group	RPP
U.S. Index	100.0
U.S. Primary Family Average	99.7
All Metro Area Average	101.9
Small Metro Area Average	95. 0
Medium Metro Area Average	97.4
Large Metro Area Average	109.3
Non-Metro Area Average	87.9
	122.9
Honolulu Index	
New York-Newark-Jersey City Index	122.2
San Jose-Sunnyvale-Santa Clara Index	122.0
Bridgeport-Stamford-Norwalk Index	121.5
Santa Cruz-Watsonville Index	121.4
Danville, VA Index	79.4
Jefferson City, MO Index	80.8
Jackson, TN Index	81.5
Jonesboro, AR Index	81.7
Rome, GA Index	82.2
Head ≥ 65 Average	99.0
Head < 65 Average	100.0
Poor Average	98.8
Income < $25,000 Average	98.5
$25,000 ≤ Income < $75,000 Average	98.6
$75,000 ≤ Income < $150,000 Average	100.3
Income ≥ $150,000 Average	104.1

Note: All RPP indices are for primary families using weighted CPS data

Table 2

Summary Statistics for Income, Poverty, and Inequality by Metro Status, 2012 (weighted CPS data)

Geographical Area	(1) Census	(2) CPS Microdata	(3) RPP Adjusted
	Mean Family Money Income		
U.S.	$82,843	$82,799	$82,719
	(322)	(403)	(394)
Metro	$86,892	$86,993	$81,501
	($1,106)	($812)	($734)
Nonmetro	$75,726	$75,801	$78,989
	($838)	($640)	($654)
	Poverty Rate		
U.S.	0.118	0.118	0.116
	(na)	(0.003)	(0.003)
Metro	na	0.137	0.117
		(0.003)	(0.003)
Nonmetro	na	0.114	0.116
		(0.002)	(0.002)
	Gini Coefficient		
U.S.	0.451	0.450	0.443
	(0.0025)	(0.0020)	(0.0020)
Metro	0.453	0.452	0.447
	(0.0028)	(0.0023)	(0.0022)
Nonmetro	0.412	0.411	0.410
	(0.0050)	(0.0045)	(0.0043)

The numbers in parentheses are standard errors, calculated using: for weighted mean family money incomes (SAS Proc Means), poverty rates (Bishop, Formby Zheng, 1997), and Gini coefficients (Bishop, Formby, Zheng, 1998).

Table 3
Summary Statistics for Income, Poverty, and Inequality by U.S. Census Region, 2012
(weighted CPS data)

Region	(1) Census	(2) CPS Microdata	(3) RPP Adjusted
	Mean Family Money Income		
Northeast	$92,651	$92,324	$84,850
	($1,498)	($1,034)	($929)
Midwest	$83,194	$83,017	$88,869
	($1,115)	($861)	($905)
South	$75,726	$75,801	$78,989
	($838)	($640)	($654)
West	$86,892	$86,993	$81,501
	($1,106)	($812)	($734)
	Poverty Rate		
Northeast	0.105	0.105	0.121
	(na)	(0.003)	(0.003)
Midwest	0.102	0.102	0.092
	(na)	(0.003)	(0.003)
South	0.132	0.132	0.121
	(na)	(0.003)	(0.002)
West	0.119	0.119	0.128
	(na)	(0.003)	(0.003)
	Gini Coefficient		
Northeast	0.455	0.453	0.448
	(0.0062)	(0.0047)	(0.0046)
Midwest	0.438	0.437	0.432
	(0.0059)	(0.0046)	(0.0046)
South	0.449	0.449	0.442
	(0.0045)	(0.0036)	(0.0034)
West	0.454	0.455	0.449
	(0.0047)	(0.0034)	(0.0035)

The numbers in parentheses are standard errors.

Table 4
Mean Family Money Income by SMSA Size, 2012
(weighted CPS data)

SMSA Size	(1) Average RPP [Housing RPP]	(2) Unadjusted	(3) Overall RPP Adjusted	(4) Housing RPP Adjusted
		Mean Family Money Income		
Small Metro	95.0	$76,917	$80,973	$81,461
	[95.0]	(927)	(986)	(998)
Medium Metro	97.0	$83,352	$85,295	$84,118
	[99.0]	(709)	(713)	(703)
Large Metro	109.0	$94,957	$86,913	$85,120
	[112.0]	(868)	(783)	(767)

The numbers in parentheses are standard errors, housing RPP's in brackets..

The unadjusted income premium for large over medium metropolitan areas is $94,957 – $83,352 = $11,605; the corresponding overall RPP-adjusted income premium is $1,618.

Table 5
OLS Estimates of Agglomeration Benefits by Metro Classification
(weighted CPS data)

	Estimated Coefficients		
	(1)	**(2)**	**(3)**
VARIABLES	**Ln(Income)**	**Ln(RPP-Adjusted Income)**	**Ln(Housing-Adjusted Income)**
Small Metro	0.084***	0.030**	0.019
	(0.012)	(0.012)	(0.012)
Medium Metro	0.134***	0.057***	0.027**
	(0.011)	(0.011)	(0.011)
Large Metro	0.223***	0.035***	-0.0006
	(0.012)	(0.012)	(0.012)
Observations	52,041	52,041	52,041
R-squared	0.334	0.326	0.324

The numbers in parentheses are standard areas
*** $p < 0.01$, ** $p < 0.05$

Table A1
Lorenz and Concentration Ordinates for U.S. Family Incomes, 2012
(weighted CPS data)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decile	L_x	L_y	(2) – (1)	C_y	(4) – (1)	C_{at}	(6) – (1)	C_{aty}	(8) – (1)
1	0.0105	0.0106	0.0001	0.0108	0.0003*	0.0135	0.0030*	0.0139	0.0034*
			(0.0001)		(0.000)		(0.0001)		(.0002)
2	0.0375	0.0381	0.0006*	0.0386	0.0011*	0.0464	0.0089*	0.0476	0.0101*
			(0.0002)		(0.0002)		(0.0002)		(.0003)
3	0.0770	0.0785	0.0015*	0.0794	0.0024*	0.0918	0.0148*	.0944	0.0174*
			(0.0002)		(0.0003)		(0.0002)		(.0005)
4	0.1298	0.1323	0.0025*	0.1337	0.0039*	0.1499	0.0202*	0.1542	0.0244*
			(0.0003)		(0.0004)		(0.0003)		(.0006)
5	0.1970	0.2009	0.0039*	0.2027	0.0057*	0.2218	0.0248*	0.2278	0.0308*
			(0.0004)		(0.0005)		(0.0003)		(.0007)
6	0.2806	0.2861	0.0055*	0.2885	0.0079*	0.3093	0.0287*	0.3173	0.0367*
			(0.0004)		(0.0006)		(0.0003)		(.0007)
7	0.3834	0.3904	0.0069*	0.3933	0.0099*	0.4152	0.0318*	0.4251	0.0417*
			(0.0005)		(0.0007)		(0.0004)		(.0010)
8	0.5112	0.5192	0.0080*	0.5223	0.0111*	0.5442	0.0329*	0.5550	0.0437*
			(0.0005)		(0.0007)		(0.0005)		(.0011)
9	0.7777	0.6853	0.0076	0.6880	0.0103*	0.7085	0.0308*	0.7182	0.0405*
			(0.0041)		(0.0049)		(0.0045)		(.0050)

Note: L_x is the Lorenz curve for family incomes, L_y is the Lorenz curve for RPP-adjusted incomes, C_y is the concentration curve for RPP-adjusted incomes ordered by unadjusted incomes (x), C_{at} is the concentration curve for (family income – federal taxes) ordered by x, and C_{aty} is the concentration curve for (family income – federal taxes)/ RPP ordered by x.

Standard errors are from Bishop, Chow, and Formby (1994).

Table A2
Generalized Gini and Concentration Coefficients, 2012
(weighted CPS data)

Parameter	(1) G_x	(2) C_y	(3) C_{at}	(4) C_{aty}
v = 2.0	0.4504	0.4395	0.4095	0.3986
v = 1.5	0.3091	0.3000	0.2767	0.2678
v = 3.0	0.5953	0.5849	0.5500	0.5393
v = 5.0	0.7223	0.7143	0.6780	0.6693

Note: G_x is the Gini coefficient for family incomes, C_y is the concentration index for RPP-adjusted incomes ordered by x, C_y is the concentration curve for RPP-adjusted incomes ordered by unadjusted incomes (x), C_{at} is the concentration curve for (family income – federal taxes) ordered by x, and C_{aty} is the concentration curve for (family income – federal taxes)/ RPP ordered by x.

Table A3
Full Summary Statistics and OLS Estimates for the Agglomeration Analysis
(weighted CPS data)

		Estimated Coeff. (Std. Error)		
	(1)	(2)	(3)	(4)
VARIABLES	Summary Statistics (Std. Dev.)	Ln(Income)	Ln(RPP Adj. Income)	Ln(Housing Adj. Income)
Small Metro	0.173	0.084***	0.030**	0.019
	(0.378)	(0.012)	(0.012)	(0.012)
Medium Metro	0.270	0.134***	0.057***	0.027**
	(0.444)	(0.011)	(0.011)	(0.011)
Large Metro	0.359	0.223***	0.035***	-0.001
	(0.480)	(0.012)	(0.012)	(0.012)
Number of Children	1.066	0.006*	0.005	0.005
	(1.181)	(0.004)	(0.004)	(0.004)
Age	49.330	0.011***	0.011***	0.010***
	(15.661)	(0.000)	(0.000)	(0.000)
Full-time Experience	28.017	0.016***	0.016***	0.016***
	(24.647)	(0.000)	(0.000)	(0.000)
Part-time	4.733	0.009***	0.008***	0.008***
Experience	(13.996)	(0.000)	(0.000)	(0.000)
Male	0.527	0.085***	0.087***	0.087***
	(0.499)	(0.008)	(0.008)	(0.008)
High School Grad.	0.464	0.332***	0.328***	0.327***
	(0.499)	(0.015)	(0.015)	(0.015)
Associates Degree	0.104	0.505***	0.499***	0.494***
	(0.306)	(0.018)	(0.018)	(0.018)
Bachelors Degree	0.202	0.793***	0.780***	0.775***
	(0.402)	(0.016)	(0.016)	(0.016)
Masters/Ph.D.	0.122	0.967***	0.948***	0.942***
	(0.327)	(0.018)	(0.018)	(0.018)
Hispanic	0.146	-0.266***	-0.286***	-0.295***
	(0.353)	(0.012)	(0.012)	(0.012)
Black	0.120	-0.392***	-0.386***	-0.382***
	(0.324)	(0.013)	(0.013)	(0.013)
Asian	0.051	-0.100***	-0.146***	-0.162***
	(0.220)	(0.019)	(0.019)	(0.019)
Other Race	0.028	-0.198***	-0.212***	-0.218***
	(0.164)	(0.027)	(0.027)	(0.027)
Constant		9.376***	9.506***	9.530***
		(0.028)	(0.028)	(0.028)
Observations		52,041	52,041	52,041
R-squared		0.334	0.326	0.324

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Endnotes

[1] Carrillo, Early, and Olsen (2014) have also published *unofficial* price indices covering all produced goods and services in all areas of the U.S. (metro and nonmetro) that extend back to 1982.

[2] For previous studies of the consequences of spatial price adjustments for U.S. poverty, see Nelson and Short (2003), Nelson (2004), Dalaker (2005), Jolliffe (2006), Beth Curran, *et al.* (2006), Renwick (2009), and Early and Olsen (2012). Most of these studies compare poverty rates across the four Census regions, the 50 U.S. states, or the 98 central cities with adjustments for housing prices. Only the last study considers variation in other prices, and it finds little difference in poverty rates by metropolitan status. To our knowledge, our paper is the first to examine the consequences of spatial price adjustment for income inequality and tax progressivity.

[3] The Supplemental Poverty Measure (Short 2015) corrects for differences in housing costs only. Renwick *et al*. (2014) and Bishop, Lee, and Zeager (2017) replace housing costs with RPPs in the construction of the Supplemental Poverty Measure.

[4] To show the importance the U.S. Census placed on the new RPPs, U.S. Secretary of Commerce, Penny Pritzker (Bureau of Economic Analysis 2014, 1) said, "For the first time, Americans looking to move or take a job anywhere in the country can compare inflation-adjusted incomes across the states and metropolitan areas to better understand how their personal income may be affected by a job change or move…".

[5] Aten, Figueroa, and Martin (2011) and Aten and Figueroa (2014) provide a detailed overview of the BEA's newly constructed RPPs. Except where otherwise noted, this discussion relies heavily on their documentation.

[6] Table 1 also provides the RPPs for the five lowest and five highest SMSAs.

[7] We replicated much of the analysis with adult equivalent comprehensive household income (including taxes and in-kind transfers such as food stamps) and obtained essentially the same results as reported below. See Bishop, Formby and Zheng (1998) for a definition of adult equivalent comprehensive household income.

[8] Appendix Table A1, columns (1) and (2), provide the family money income Lorenz ordinates by decile, before and after RPP adjustment.

[9] We also made similar adjustments in poverty rates for racial minorities. Recall from Table 1 that the RPPs for Asians and Hispanics are above the U.S. average. RPP adjustments increase the Hispanic poverty rate from 23.4 percent to 24.3 percent and the Asian poverty rate from 9.3 percent to 10.3 percent.

[10] For a standard treatment of these issues, including tax progressivity, see Lambert (1989). The following analysis is based on the standard Gini coefficients, however, we report the underlying decile Lorenz and concentration ordinates in Appendix Table A1 and some generalized Gini coefficients in Table A2.

[11] We obtain a re-ranking effect of $C_y - G_y = 0.4395 - 0.4128 = 0.0267$.

[12] The change in vertical equity in the federal tax system due to RPP adjustment is similar in magnitude to the effect of tax noncompliance; see Bishop, Formby, and Lambert (2000).

[13] We adapt their specification by using incomes in places of wages and dropping the time dimension and the fixed-effects term, which we cannot estimate with CPS data. Many of their results also constrain this term to be zero (Glaeser and Mare 2001, 328).

[14] The full set of results, along with summary statistics from the estimation of equation (5), are provided in Appendix Table A3.

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[15] We calculate the percentage earnings differentials using the method of Holversen and Palmquist (1980).

[16] F-tests for the equality of the coefficients on *Metro 1* and *Metro 3* fail to reject the null hypothesis that these coefficients are statistically indistinguishable at any conventional level of significance.

[17] The housing index (RPP_H) is constructed as $RPP_H = (0.41)BEA_H + (0.59)100$, where BEA_H is the housing component of the BEA's overall RPP. The weights 0.41 and .059 come from the 2013 CPI weights for housing and other goods, respectively. That is, we are assuming for this particular exercise that only housing prices differ across regions; all other prices are at the national average (100).

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