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ORIGINAL ARTICLE

Income and cost of living: Are less equal places more costly?

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ABSTRACT

Objective: This study empirically investigates the impact of economic inequality on the cost of living in U.S. metropolitan areas.
Methods: Using a special Census tabulation, a standard cost-of-living model is sequentially augmented with measures of poverty and income inequality in a cross-sectional regression analysis of 90 metropolitan areas; interaction and regional effects are also explored.
Results: Higher costs of living are associated with increasing economic inequality, especially in the distribution of metropolitan income. The effects of household poverty are significant but less consistent.
Conclusions: Reducing economic inequality would produce benefits enjoyed by all metropolitan residents via lower living costs. The benefits are likely to be greater in large, fast growing areas where income disparities are pronounced.

KEYWORDS
cost of living, inequality, metropolitan

INCOME AND COST-OF-LIVING: ARE LESS EQUAL PLACES MORE COSTLY?

Economic inequality, within and between the nation's metropolitan areas, has become a pressing policy issue. While poverty has been a persistent problem (Teitz and Chapple, 1998) and income inequality by race (Hero and Levy, 2016) and gender (Hoffman, 2014) are well documented, the work of Chetty et al. (2014) has put inequality at the top of the policy agenda in many cities.[1] At the same time, inequality has become starker as the gap between rich and poor widens. Both features of urban life—poverty and increasing wage disparities—impose social costs: Poverty alleviation efforts are largely shouldered by the nonpoor, and rapid growth in wages among those at the top of the income distribution puts upward pressure on urban housing and other markets affecting all urban consumers, city and suburban, poor and nonpoor. We should expect, then, the cost of living in cities with a greater incidence of economic inequality to be higher than comparable cities with less inequality. There is reason to believe this relationship might be stronger

[1] Throughout the article, the terms metropolitan area, metro area, and city are used interchangeably. They all refer to census-defined metropolitan statistical areas.

in larger urban areas (Gleaser, Resseger, and Tobio, 2009), yet the literature addressing cost-of-living has yet to systematically address this possibility head on.

Given the importance of cost-of-living to economic well-being (Curran et al., 2006) and its distinctive geographic variation (Campbell and James, 2021), general interest in the subject is not surprising. Households consider living costs when choosing between competing job offers or making migration decisions (Foley and Angellari-Dajci, 2015). Firms consider cost-of-living differentials when setting compensation packages for their employees and executives (Fournier and Rasmussen, 1986; Francis et al., 2016; Zong, Gao, & Zhou, 2019), and some state governments adjust spending formulas for local living costs (Fowler, 1996; Silvernail & Sloan, 2009). To be sure, cost-of-living plays an important mediating role between income and economic well-being via its impact on household purchasing power.

Since the late 1970s, a growing share of income has accrued to wage earners at the top of the wage distribution, a pattern that is both persistent and geographically uneven. Abel and Dietz (2019) report that in 2015, the top 5 percent of wage earners received more than seven times those in the lower 10 percent; among the upper 1 percent, income was 25 times greater than the bottom 1 percent (Sommeiller, Price, and Wazeter, 2016). One way in which these trends can affect place-specific costs of living is through the housing market. Because Americans have a relatively high elasticity of demand for housing (Voith, 2000), income growth can quickly translate into upward pressure on the price of housing and other goods and services. Distributional issues emerge when income growth is concentrated in the upper deciles of the wage distribution, raising housing and other costs for all metropolitan residents including those at the lower end of the income distribution (also see Albrecht & Albrecht, 2007). To the extent these demand shifts materialize and do so in particular places (e.g., metropolitan areas with substantial high-wage financial and technology sectors), the impact of income inequality on costs of living should be measurable and locationally specific. With one notable exception (Cebula and Todd, 2004), the longstanding interest in the dynamics of urban growth has not been met with a systematic treatment of income inequality and its relation to the cost of living.[2] This article helps fill that void.

It is hypothesized that the cost of living is an increasing function of economic inequality. The hypothesis is tested on a sample of 90 U.S. metropolitan areas. A standard cost-of-living model is sequentially augmented with measures of poverty and income inequality using a special Census tabulation of a key measure of income inequality.

The remainder of this article is organized as follows: A review of the cost-of-living literature is presented next, followed by a discussion of economic inequality, both of which inform the main hypothesis and selection of variables. Models and data are then presented, followed by a discussion of results. The article concludes with thoughts about the implications for development policy.

Background on cost-of-living research

From 1966 to 1982, the Bureau of Labor Statistics produced a cost-of-living index for selected large metropolitan areas. Although the number of metropolitan areas covered changed from 39 to 24, the data series spawned a veritable cottage industry addressing regional variation in costs of living. Some work focused on utility theory and index construction (e.g., Kokolski, 1989; Koo, Phillips and Sigalla, 2000), others focused on correlates with living costs as a means to develop analogous indexes for states, smaller metropolitan areas, and counties (e.g., McMahon and Melton, 1978). The resulting regression-based analyses served at least three important purposes: they (1) provided a consistent system by which the cost of living in out-of-sample areas could be estimated; (2) could be used to determine the relative importance of different economic, demographic, and institutional factors on living costs; and (3) could be used to estimate the impact of particular events or conditions on living costs. In doing so, broader questions about living costs and the impact of various exogenous variables (e.g., natural amenities, net migration), policy

[2] In Cebula & Todd (2004), the percentage of households with income over $100,000 was used to explain cost-of-living differentials among Florida counties. The estimated coefficient was positive and highly significant.

contexts (so-called "right-to-work" legislation), as well as changes in the economic landscape could be addressed.

Although there are several cost-of-living measures available (see Jolliffe, 2006 for a review), the most widely used cost-of-living index (COLI) is produced by the Council for Community and Economic Research (C2ER). Since 1968 (when it was known as the ACCRA cost-of-living index), it has reflected the average cost of a fixed bundle of goods and services in participating U.S. urban areas. Importantly, COLI provided a large sample of consistently compiled cost indexes on which out-of-sample estimates for states, counties, and other localities could be estimated.

Representative examples of early regression-based work include Haworth and Rasmussen (1973), McMahon & Melton (1978), Cebula (1980), and Ostrosky (1983). Like a variation on a theme, virtually all cost-of-living studies included demand-side factors expected to be positively related to living costs, including population, population change, and some measure of income—wages, personal income per capita, or median household income. Reflecting the fact that most household consumption is devoted to normal goods, these factors were invariably positive and significant predictors of living costs. It was not uncommon to find population density used as an explanatory variable to reflect the idea that increasing densities also increase costs associated with congestion and other externalities (Cebula, 1980).[3] Discussed further below, some measures of natural amenities, usually reflecting temperature extremes, entered most models, though McMahon & Melton (1978) suggested that amenities should be reflected in housing costs and need not enter the model as a separate variable (see also McMahon, 1991). Some of the early works also included a measure of tax burden (either tax rate, per capita tax, or taxes paid by business) hypothesized to positively relate to living costs. The work of Kirk (1982) is also notable because rather than focusing on significant predictors of living costs, he examined trends in their coefficient of variation from 1969 to 1978. In doing so, he found evidence that living costs across metro areas had diverged over time, especially with respect to housing, a finding consistent with the notion that prices and costs get bid up when increasing demand is coupled with inelastic supply in land and housing.

Unionization and a state's "right-to-work" (RTW) status also became a standard part of cost-of-living models. While unionization has been positively associated with a more equal distribution of regional income (Hu and Hanick, 2018), RTW states are known to have lower average wages (Gould and Kimball, 2015) which should dampen demand pressure on the cost of living. Interestingly, the mechanism by which RTW states produce lower average wages is the same mechanism by which states with higher rates of union membership produce more equal wage distributions. That is, much of the wage premium associated with labor unions accrues to workers with lower skill levels helping to both raise average wages and compress the resulting wage distribution (Card, 1996). However, the precipitous decline in union membership and a growing number of RTW states lacking the wage supports for lower-wage workers likely dampens cost-of-living via lower average wages. Theoretically then, because states with RTW legislation generally have lower unionization rates, RTW should be negatively associated with living costs.

In virtually every state-level analysis, RTW is indeed negative and significant (e.g., Cebula, 1980; Cebula et al., 2017), but empirical analyses at the metropolitan level are not so consistent. Ostrosky (1983), for example, found the expected significant influence of unionization on cost-of-living but Campbell & James (2020) did not find similar significance in their recent study of 96 metropolitan areas. More interesting still, when Hogan (1984) tested RTW against the individual components of living costs (food at home, shelter, transportation, etc.) statistical results were highly mixed; of the 12 household spending categories examined, RTW was significant in only three—food at home, "other" costs, and income taxes. Even though inclusion of an RTW dummy variable has become part of the standard cost-of-living model, empirical results have been inconsistent.

[3] It should be noted that density, coupled with city size, is an indicator of agglomeration and scale economies. If city size contributes to economies of scale and other Marshallian-type agglomeration benefits, then costs might actually fall with increasing density. On the other hand, the income effects of increasing returns to scale and skill could easily outweigh economies of scale, leading to higher prices overall. This is the gist of the argument made below.

Most cost-of-living studies recognize amenities, typically natural amenities, as important predictors of living costs. Clearly, the nontraded place-specific character of natural amenities helps differentiate one place from another. Natural amenities including pleasant climate, attractive and varied landscapes, and access to leisure and recreational activities, along with the necessary provision of goods and services to accommodate their consumption are important parts of tourism and economic development in many parts of the country. Central to amenity valuation is the fact they are location-specific, limited in supply, and subject to a high elasticity of demand (Marcouiller and Glendenning, 2005). In one of the more extensive investigations of amenities and quality of life, Deller et al. (2001) examined 53 amenity variables finding that "all statistically significant amenity attributes are positively related to economic growth. Not a single statistically significant negative coefficient was uncovered" (p. 363). The connection between natural amenities, growth, and, thus, cost-of-living is clear. Further, endogenous amenities (e.g., fine dining, cultural attractions, professional sports, etc.), or quality public services that have amenity-like attributes can have similar impacts (see Broxterman et al., 2019; Gyorko & Tracey, 1991; Diamond, 2016).

Just the same, natural amenities deserve special attention because they hold a somewhat curious place in the cost-of-living literature. On one hand, there is substantial theoretical literature addressing the interplay of amenities with wages, housing costs, migration, and employment growth (Graves and Linneman, 1979; Graves & Knapp, 1988). On the other hand, the treatment of amenities in empirical cost-of-living models is quite rudimentary. Theoretically, compensating differentials are frequently asserted such that the amenity value of place is capitalized into land and labor; ceteris paribus, housing costs are higher and wages are lower in high-amenity locales (Roback, 1988). In other frameworks, the connection between amenities and income inequality rests in the fact that amenities are normal "goods" desirable to both firms and workers. Whether as a matter of cause or effect, amenity-rich cities have become especially productive places, attractive to high-skill high-wage workers (Glaeser et al., 2001). The benefits of urban agglomeration, coupled with skill-biased technical change (SBTC) have simultaneously served to increase demand for and relative returns to high-skill workers, dampen demand for middle-wage workers, and bifurcate wage distributions (Autor et al., 2008). Productivity gains in cities specializing in high-skill work have thus produced widening gaps in metropolitan wages and well-being. As Albouy (2016) has shown, demand for amenities rises with local productivity and "the most productive and valuable cities are typically coastal, sunny, mild, and large" (p. 477). Augmenting productivity dimensions are the consumption-based preferences of high-wage workers for amenity-rich cities. Because demand for amenities from high-wage workers is income elastic, we should expect SBTC-induced wage divergence to be associated with amenity-rich cities. Further, if there are supply constraints in local housing markets, cities experiencing increasing shares of skilled workers should also experience increasing housing costs (Moretti, 2010).

The extent to which amenities are fully reflected in the cost of living, however, is still a matter of both theoretical and empirical debate. Cebula (1980), for example, suggests that migrants consider wages and amenities *in addition to* cost-of-living differentials even if only in an approximate way (see also Cebula and Alexander, 2006). Winters (2009) shows that whether wages and housing costs equilibrate across regions depends on how housing costs are measured (median home prices vs. housing rent). Regardless of the theoretical stance, natural amenities are overwhelmingly captured through variables as simple as heating/cooling degree days, miles of coastline, and so on (though Cebula & Toma (2008) included a measure of toxic chemical releases as a dis-amenity in their state-level study).

Poverty, inequality, and cost-of-living

Given the close connection between economic performance (population, employment, and income growth) and the relative cost of living, it is surprising that the treatment of household poverty or the distribution of regional income, both locally and interregionally, has received so little attention in the cost-of-living literature. In their study of amenities and quality of life, Deller et al. (2001) show that higher levels of income inequality were associated with slower rates of population growth. Marcouiller et al. (2004) reach a similar conclusion with respect to amenities and the "hollowing-out-of-the-middle-class" hypothesis. In metropolitan areas, it is increasingly recognized that economic performance is not merely related to traditional location factors—access to materials, markets, and transportation. Rather, metropolitan growth is at least partially tied to economic, demographic, and spatial structure, each of which can affect metro inequality. There are at least three schools of thought on the relationship between structure, inequality, and metropolitan growth.

First, economic performance and the resulting distribution of income within and among metropolitan areas are intimately tied to its mix of industries. The exceptional growth of financial and technology centers in New York, Boston, Charlotte, Austin, San Francisco, and San Jose, for example, are well known. The benefits of city size, agglomeration, increasing returns to scale, and skill in knowledge-intensive industries produce an ever-widening disparity in metropolitan income.

Second, from a demographic perspective, the severity and persistence of poverty are known to inhibit economic growth (Gottlieb, 2000). Part of the poor economic performance of central cities is related to the direct (e.g., public health) and indirect (e.g., police and fire protection) public costs of poverty alleviation efforts. Joassart-Marcelli et al. (2005), for example, show that concentrated poverty in Southern California cities increase expenditures for poverty and nonpoverty functions. The resulting fiscal stress is exacerbated because many of the added public costs of poverty are uncompensated by state or federal government.

Third, another view of poverty makes a complementarity argument with respect to skill and labor force participation; that is, high-, medium-, and low-skill labor are complements in production, and to the extent that poverty limits labor force participation, economic performance is sacrificed because complementarity in production is sacrificed. A similar complementarity argument is made with respect to spatial structure—since cities and their suburbs are complements in production and consumption, regional imbalances or mismatches within metropolitan areas can lead to slower growth (Voith, 1998; Li et al., 2013). While poverty is clearly an imperfect measure of inequality, it tends to correlate with several other variables related to living costs.

Beyond poverty, other measures of economic inequality such as Gini coefficients or the entropy index have been used extensively as direct measures of inequality. The 90/10 income ratio—a measure comparing the income of the top 90th percentile of households to that of the 10th percentile—is also used commonly used because of its ease of interpretation. A 90/10 income ratio of 8.0, for example, indicates the income of the top 10 percent of households is eight times greater than that of the bottom 10 percent. While useful, these measures, by themselves, do not indicate where in the income distribution inequality occurs. That is, whether or not changes in inequality are due to income growth at the higher or lower ends of the wage distribution cannot be determined by examining their changes over time. To address this shortcoming, Glassman (2017) examined the 90/10 income ratio in relation to the 50/90- and 50/10-income ratios to determine if widening income disparities are the result of changes in the bottom half or top half of the income distribution. His meticulous assessment of income disparity among U.S. metropolitan areas from 2005–2015 demonstrates that increases in the 90/10 ratio were the result of income growth in the upper half of the distribution. Further, changes in inequality were (a) positively associated with metropolitan size, educational attainment, and the prevailing poverty rate and, thus, (b) not uniform across metro areas. Abel and Dietz (2019) confirmed this result, attributing the growing disparity to the interplay of increasing demand for (and returns to) skill, technological change, globalization, and the selective migration of skilled workers to large metropolitan areas specializing in knowledge- and information-intensive activities. Glaeser et al. (2009) and Baum-Snow & Paven (2013) come to the same conclusion noting that returns to skill explain as much as one-third of metro income equality, especially in large metro areas with employment concentrations in sectors with high factor ratios of skilled-to-unskilled workers. The result is that the least unequal places are those with sluggish economies (especially those in the Midwest and Upper Great Lakes regions), while inequality is greatest in vibrant economies where demand for skill and agglomeration is strongest. In short, economic inequality appears to be a byproduct of metropolitan growth.

From the cost-of-living perspective, changes in income inequality as measured by the 90/10 ratio, likely exert upward pressure on the cost of housing and other goods and services. If demand pressure from the 90th percentile of income earners is sufficient to affect metropolitan prices overall, those regions with high (or growing) 90/10 ratios should also be those with relatively high (or growing) costs of living. The distributional and equity issues are clear: Because households in poverty or those in the 10th percentile of the regional income distribution are relatively immobile and bare amenity costs whether or not they value them, growth spurred by high-skill, high-wage earners can disproportionately affect regional living costs for those in the lower half of the income distribution, including households in poverty. As is hypothesized here, we should expect both the prevalence of poverty and the size of the 90/10 ratio to be positively related to metropolitan costs of living.

Models and data

To test the impact of inequality on metropolitan costs of living, a standard cost-of-living model comprised of predictors commonly found in the literature is presented. Below, this is called the "Base Model." From there, three measures of income inequality are sequentially introduced to determine their separate influence while controlling for factors included in the Base Model. Interaction terms are also tested, and as a further check on robustness, regional effects are included in the last iteration of the analysis. The models take the following general form:

$$\textit{Base Model}: COLI_i = \alpha + \beta_i X_{ij} + \varepsilon \tag{1}$$

$$\textit{Inequality Models}: COLI_i = \alpha + \beta_i X_{ij} + \beta_i X_{ik} + \varepsilon \tag{2}$$

$$\textit{Regional Model}: COLI_i = \alpha + \beta_i X_{ij} + \beta_i X_{ik} + \beta_i X_{il} + \varepsilon \tag{3}$$

where $COLI_i$ is the C2ER cost-of-living index for 2018, X_j are metropolitan characteristics commonly found in standard cost-of-living models, X_k are measures of metropolitan inequality, and X_l are regional dummy variables reflecting nine broad Census regions. β_j, β_k, and β_l are vectors of regression coefficients; ε is the error term. The models are estimated for 90 metropolitan areas in the contiguous U.S. with populations above 600,000.

The dependent variable, $COLI_i$, is designed to reflect inter-urban differences in the average cost of maintaining a "standard of living appropriate for moderately affluent professional and managerial households" (i.e., those with income in the top quintile for the area) (C2ER, 2017:1.2). The composite index reflects the average cost of 57 items, grouped into six categories (groceries, housing, utilities, transportation, health, and miscellaneous services), each of which are weighted on the basis of data from the U.S. Bureau of Labor Statistics' 2007 *Consumer Expenditure Survey*. The number of areas included in the index has gradually grown and now typically covers more than 250 urban areas and more than 70 percent of the U.S. population (C2ER, 2017).

Independent variables, along with their expected signs, are listed in Table 1. POP is the natural log of 2018 metropolitan population and HHINC is metro-wide median household income (in thousands), both of which are expected to be positively related to cost-of-living. RTW is a dummy variable indicating whether the metro area is in a right-to-work state (1 = yes). In those few cases where the metro area crosses a state line with a different right-to-work status, the location of the primary city is used to determine RTW. The expected sign on RTW is negative.

Like most all cost-of-living models, the Base Model includes an amenity measure. Here, the Base Model differs slightly from the usual set-up. Natural amenities have been variously treated in the literature and, almost without exception, have been represented by a one-dimensional measure—usually heating degree days or cooling degree days—which is typically a significant predictor of COLI. A better measure, and one not previously used in the cost-of-living literature, is McGranahan's (1999) amenity score.

TABLE 1 Variables, variable definition, and expected signs

Variable name	Definition	Expected sign
POP	Total population (thousands), 2018	POS
HHINC	Median household income (thousands of dollars), ACS 2014–2018	POS
AMENITY	Amenity scale, 1–7 (McGrannahan, 1989)	POS
RTW	Right-to-work state, 1/0	NEG
POVRATE	Household poverty rate, ACS, 2014–2018	UNCERTAIN
GINI	Gini coefficient of metro household income, 2015	POS
RATIO90_10	Income ratio: Ratio of income to the 90th percentile of households to the 10^{th} percentile, 2015	POS
Region	9 Census Regions, reference region = New England	

Descriptive statistics can be found in the Appendix (Table A).

McGranahan has, for every county in the contiguous U.S., computed an amenity score that combines six separate measures into a single amenity value. The score gives equal weight to each of the following standardized variables: mean January temperature; mean hours of sunlight in January; mean July temperature; mean relative humidity in July; a topography code that characterizes the physical landscape (flat plains, open hills, high mountains, etc.); the percent of the county's area covered by water. The score ranges from 1–7, with higher scores indicating more desirable combinations of natural amenities. Since the presence of natural amenities is capitalized into land and housing costs thereby influencing COLI, the expected sign on AMENITY is positive.

The inequality model of Equation (2) allows the impact of different inequality measures on cost-of-living to be tested while controlling for other factors included in the Base Model. The three different measures of metropolitan area inequality are the household poverty rate (POVRATE), the Gini coefficient (GINI), and the 90/10 income ratio (RATIO90_10). POVRATE was calculated using 2014–2018 five-year averages as reported in the American Community Survey (ACS) and available from the National Historical Geographic Information System (see Manson et al., 2020). Higher rates of poverty might reduce demand for goods and services and thereby lower the cost of living. Alternatively, the costs of poverty alleviation, direct and indirect, could raise overall costs. Consequently, the expected sign on POVRATE is uncertain. GINI is a common inequality metric hypothesized to be positively related to COLI. Similarly, the sign on RATIO90_10—the ratio of income accruing to households in the 90th percentile of the income distribution compared to that accruing to the 10th percentile—is expected to be positive.

It should be noted that while other studies of wage disparity and income inequality have used IRS data or the 5 percent sample from IPUMS to calculate the 90/10 ratio, this study uses a special tabulation from the 1-year American Community Survey (Glassman, 2017). Though rarely used to study income inequality, the 1-year ACS data presents certain advantages over IRS or data available through IPUMS. Based on a larger sample than IPUMS, the 1-year ACS tabulation is thought to be a more accurate measure of the 90/10 ratio. Further, because it captures the income of non-filers in the lower end of the income distribution, the 1-year ACS tabulation provides a more complete picture of the income distribution than IRS data. The downside is that Census confidentiality requirements restrict release of this tabulation of the 90/10 income ratio to large metro areas only. Consequently, 90 metropolitan areas in the contiguous U.S. with populations in excess of 600,000 are examined here. To ease interpretation, all inequality variables enter the model as standardized z-scores. Variable names are adjusted to reflect this (i.e., ZPOVRATE, ZGINI, ZRATIO90_10).

Finally, to examine any systematic regional effects of inequality on cost-of-living, Equation (3) includes dummy variables corresponding to the nine broad Census regions (the omitted reference region is New England).

TABLE 2 Highest and lowest cost of living metropolitan areas, 2018

Top 15 COLI		Bottom 15 COLI	
Los Angeles, CA	163.7	Jackson, MI	89.5
San Francisco, CA	160.3	Battle Creek, MI	89.0
New York, NY	155.6	Mansfield, OH	88.7
San Jose, CA	155.3	Midland, MI	88.6
Bridgeport, CT	147.5	Pine Bluff, AR	88.5
Napa, CA	141.2	Beaumont, TX	88.4
San Diego, CA	140.8	Youngstown, OH	88.4
Boston, MA	137.7	Laredo, TX	87.9
Santa Rosa, CA	136.0	Flint, MI	87.5
Santa Cruz, CA	135.4	Saginaw, MI	87.4
Sacramento, CA	134.2	Gulfport-Biloxi, MS	87.3
Baltimore, MD	133.8	Muskegon, MI	87.2
Oxnard, CA	133.2	Brownsville, TX	84.1
Santa Maria, CA	133.1	McAllen, TX	82.6
San Luis Obispo, CA	132.0	Yuma, AZ	81.0

Source: C2ER.

In addition to the descriptive statistics (see Appendix), Tables 2 and 3 illustrate some characteristics of the dependent variable as well as the inequality variables of interest. Table 2 includes a list of the 15 most and 15 least expensive metro areas as measured by COLI in 2018. Most striking is the range of values implying that the most expensive cities (Los Angeles and San Francisco) are about twice as costly as those with the lowest costs of living (McAllen, TX and Yuma, AZ); 11 of the 15 most expensive metros are in California. Large metro areas are generally more expensive than smaller ones and many metros with low costs of living are boarder cities in Texas or parts of the Midwestern manufacturing belt.

Table 3 shows the top and bottom 15 cities in terms of the inequality measures. Metro names in bold are those that appear in more than one list in Table 3. Several of the top 15 COLI metros from Table 2 are represented in Table 3 but only one low COLI metro (McAllen, TX) is represented. Most notable is the lack of overlap between high/low poverty metros and other indicators of inequality; there is far more overlap between high/low Gini coefficients and the 90/10 income ratio. Two thirds of the metro areas with high/low Gini coefficients are also among the metros with high/low 90/10 ratios. Consistent with observations from the literature, many of those with high Gini coefficients or 90/10 income ratios are larger metros with sizable sectors in technology, finance, or other advanced producer services. Metros on the low end are disproportionately homes to manufacturing or have a sizable government presence via state capitols and military installations. Table 3 suggests that the Gini coefficient and the 90/10 income ratio are more closely related to each other than to the poverty rate. Simple correlation bears this out. The correlation between POVRATE and GINI is 0.515; the correlation of POVRATE with RATIO90_10 is 0.503 while the correlation between GINI and RATIO90_10 is 0.877. It appears that the Gini coefficient and the 90/10 income ratio are reflecting a similar aspect of inequality, distinct from processes associated with poverty.

Results and analysis

Regression results for the Base Model and Inequality Models are presented in Table 4. All models perform well, explaining at least 75 percent of the variation in COLI, all have the expected signs, and all are free

TABLE 3 Inequality measures by metro area, 2015

Metro	Poverty rate	Metro	Gini coeff.	Metro	90/10 ratio
Top 15					
McAllen, TX	29.1	**Bridgeport, CT**	0.458	**New York, NY**	9.62
Brownsville, TX	28.9	**Miami, FL**	0.452	**Bridgeport, CT**	9.44
Laredo, TX	28.0	**New York, NY**	0.450	**McAllen, TX**	9.27
Valdosta, GA	25.1	**McAllen, TX**	0.443	**San Francisco, CA**	9.03
Las Cruces, NM	25.1	**Houston, TX**	0.433	**Miami, FL**	8.64
El Centro, CA	24.5	**Los Angeles, CA**	0.432	**Los Angeles, CA**	8.50
Albany, GA	22.9	**San Francisco, CA**	0.422	**Houston, TX**	8.41
College Station, TX	22.8	**Fresno, CA**	0.419	**New Orleans, LA**	8.37
Monroe, LA	22.5	Memphis, TN	0.418	**Fresno, CA**	8.33
Visalia, CA	22.3	Cape Coral, FL	0.417	Baton Rouge, LA	8.21
Auburn, AL	22.1	**Chicago, IL**	0.416	Boston, MA	8.15
Athens, GA	22.1	Dallas, TX	0.415	Philadelphia, PA	8.15
Greenville, NC	22.1	Knoxville, TN	0.415	San Jose, CA	8.07
Macon, GA	21.9	**New Orleans, LA**	0.413	Memphis, TN	7.97
Bloomington, IN	21.3	Phoenix, AZ	0.413	**Chicago, IL**	7.91
Bottom 15					
Oxnard, CA	8.7	Rochester, NY	0.377	Greensboro, NC	6.14
Minneapolis, MN	8.6	Greenville, SC	0.377	Boise City, ID	6.11
Rochester, MN	8.5	**Des Moines, IA**	0.377	Deltona, FL	6.10
Ogden, UT	8.5	Lakeland, FL	0.376	**Virginia Beach, VA**	6.07
The Villages, FL	8.5	**Raleigh, NC**	0.372	**Raleigh, NC**	6.05
Midland, TX	8.3	Worcester, MA	0.370	**Des Moines, IA**	6.02
Appleton, WI	8.0	**Virginia Beach, VA**	0.368	**Omaha, NE**	5.96
Sheboygan, WI	7.9	**Madison, WI**	0.367	**Albany, NY**	5.95
Manchester, NH	7.8	**Omaha, NE**	0.366	**Allentown, PA**	5.90
Gettysburg, PA	7.8	**Allentown, PA**	0.366	**Colorado Springs, CO**	5.82
San Jose, CA	7.8	**Minneapolis, MN**	0.366	**Madison, WI**	5.71
Napa, CA	7.7	**Colorado Springs, CO**	0.364	**Minneapolis, MN**	5.66
Washington, DC	7.6	**Albany, NY**	0.362	Grand Rapids, MI	5.57
California, MD	7.5	**Salt Lake City, UT**	0.362	**Salt Lake City, UT**	5.46
Barnstable Town, MA	7.2	**Ogden, UT**	0.329	**Ogden, UT**	4.83

Note: Poverty rate is calculated from 2014–2018 ACS data, Gini coefficient and 90/10 ratio are for 2015. Entries in bold appear indicate metro areas that appear in more than one column.
Sources: NHGIS/ACS, U.S. Census Bureau.

from multicollinearity. Because of heteroscedasticity in the residuals, statistical significance is determined using robust standard errors. Variables used in the Base Model are consistent with similar models found in the cost-of-living literature. It provides a basis for evaluating the impact of inequality measures and serves as a check for overall statistical stability of subsequent models. Consistent with similar analyses, POP and HHINC are positive and significant, reflecting the tendency for larger and more affluent metro areas to face higher prices due to their higher levels of demand. The coefficient on POP implies that the cost of

TABLE 4 Base model and inequality models

	Base Model	Poverty Model	Inequality models: Gini Model	90/10 Model
Intercept	−2.102	−12.499	35.634	29.570
	(27.695)	(27.652)	(22.340)	(23.027)
POP	4.149**	3.710*	1.324	1.761
	(2.149)	(2.020)	1.647	(1.704)
HHINC	0.607***	0.861***	0.700***	0.673***
	(0.097	(.227)	0.075***	(.082)
AMENITY	4.555***	4.077***	3.844***	3.995***
	−0.855	(0.917)	(0.843)	(.817)
RTW	−9.846***	−8.430***	−10.459***	−8.585***
	(1.901)	(2.1995)	(1.776)	(1.736)
ZPOVRATE		4.021		
		(3.427)		
ZGINI			4.291***	
			(1.023)	
ZRATIO90_10				4.541***
				(1.052)
Adj R2	0.753	0.776	0.813	0.815
F	68.995	62.578	72.979	79.572

Note: ZPOVRATE, ZGINI, ZRATIO90_10 and are expressed as standardized z-scores. All VIF less than 2.0 except HHINC and ZPOVRATE in Poverty Model where VIF values are 3.401 and 2.511.
Robust standard errors in parentheses.
***$p = 0.01$. **$p = 0.05$.*$p = 0.10$.

living increases by about 1 percent for each additional 63,000 residents in the sample. Likewise, cost-of-living is an increasing function of household income as COLI is estimated to increase by 0.607 percent for every thousand dollars of income. Assessed at their mean values, a 1 percent increase in household income (from $63,110 to $63,741) would cause metropolitan living costs to rise by about 0.56 percent (from 109.3 to 109.91).

The first important set of results is that cost-of-living is an increasing function of natural amenities and metros located in states with right-to-work legislation face living costs that are about 10 percent lower than those in states without such legislation.; Perhaps most important is that cost-of-living is somewhat inelastic with respect to household income. Part of this inelasticity stems from the fact that while housing costs show significant inter-city variation, local retail prices of non-housing goods and service are not necessarily higher in high-wage metros (c.f. Moretti, 2010 and Choi et al., 2020). If so, changes in median household income will not correspondingly translate to proportional change in the cost of living. Further, the use of median household income as a measure of local purchasing power, while common in the cost-of-living literature, might mask important variations in consumer behavior at different points in the income distribution. Argente and Lee (2021), for example, show that the ability of households to shift their spending patterns in light of changing prices varies by income level: higher income households, with greater flexibility in consumption, can more easily than lower income households shift spending by substituting across varieties, changing the quality of goods and services they consume, and otherwise alter their shopping behavior. In doing so, they show that "the relationship between quality (measured by unit price paid) and income is flat for households below the median income" (p. 915). That households with lower income are less able than higher income households to adjust their expenditure patterns in the face of rising relative prices not only helps explain why cost-of-living is somewhat inelastic with respect to median household income, but might also carry broader implications for regional development policy which are addressed below.

The Base Model is consistent with those found in the literature and offers a good point of departure. Sequentially, the Inequality Models enter the metro-specific household poverty rate, Gini coefficient, and 90/10 income ratio to the Base Model. Inclusion of the poverty rate improves explained variance only marginally but is not a significant predictor. It is possible that costs of poverty alleviation are not sufficiently large to affect area-wide living costs; it is also possible that the added costs of poverty alleviation are off-set by lower levels of demand such that its impact on aggregate living costs is negligible. Results for the Gini Model and the 90/10 Model are consistent with expectations—both inequality measures improve model fit, and both are highly significant. Expressed as standardized *z*-scores, the coefficients imply changes in COLI given a one standard deviation change in the predictor variable. It is notable that the magnitude of the coefficients across each inequality variable is quite similar. Generally, each additional standard deviation in either the Gini coefficient or the 90/10 ratio is associated with about a 4.0–4.5-point increase in COLI providing the first evidence that higher levels of economic inequality are generally associated with higher costs of living. Viewed in light of the results presented by Glassman (2017) and Abel and Deitz (2019), the evidence so far suggests that higher living costs are being driven by income disparities in the upper portions of the wage distribution.

The possibility that inequality might interact with city size is frequently suggested, so interaction terms are introduced in Table 5. Both ZPOVRATE and its interaction with metro population, POPxPOV, are positive and significant as expected. With a standard deviation of 3.18, reducing metropolitan poverty by three percentage points would lower the overall cost of living by about 8 percent in the sample metropolitan areas. The positive and significant interaction term suggests the benefits of poverty reduction increase with increasing metro size. Beyond the impact of sheer city size, part of the interaction effect is likely due to the added costs of alleviating concentrated poverty (Sampson, 2019), which is both more prevalent and suburbanizing more quickly in large metropolitan areas, especially those large metros of the Northeast and Midwest (Kneebone and Holmes, 2016). ZGINI and POPxGINI work similarly. Increasing (decreasing) income inequality, especially in larger metro areas, is associated with increasing (decreasing) COLI. The magnitude of COLI changes from the 90/10 income ratio is similar, reflective of the close relationship between the 90/10 ratio and the Gini coefficient.

Taken together, results from Tables 4 and 5 suggest that area-wide cost-of-living would fall by 1.25–2.50 percent for each percentage point reduction in household poverty. For the median metropolitan area in the sample (population of 1.266 million, $60,940 in household income), aggregate economic welfare would increase by at least $382 million and perhaps as much as $768 million. Even if only half of the welfare gain was subject to local cost-of-living differentials, the impact would be notable. These cost savings, of course, would be enjoyed by all residents of the metropolitan area, not just those previously in poverty. Similar efficiencies would result from more equal income distribution.

Finally, to control any regional variation that might affect the results so far, the models are tested with nine broad Census regions included (New England is the reference region). The results, shown in Table 6, also include the Base Model for comparison. Controlling for geographic region, nearly all Base Model control variables behave as expected. The only exception is RTW. Earlier results above, like those in the literature generally, found right-to-work status to lower COLI by about 7–10 percent. After controlling for region, however, the effect of RTW on COLI disappears. Given that exactly half of the metropolitan areas in this sample are located in right-to-work states, the result is reasonably robust. It is entirely possible that RTW and its impact on COLI, captures, or is somehow related to, other factors that vary geographically "rather than (or, in addition to) the impact of labor markets on living costs" (Ostrosky, 1983:350).

TABLE 5 Interaction models

	Poverty Model	Gini Model	90/10 Model
Intercept	−23.277	63.053***	14.379
	(26.277)	(17.596)	(18.868)
POP	3.654**	−0.703***	1.662
	(1.747)	(1.282)	(1.371)
HHINC	1.127***	0.715***	0.917***
	(0.218)	(0.071)	(0.207)
AMENITY	3.468***	3.794***	4.016***
	(0.837)	(0.770)	(0.787)
RTW	−7.889***	−10.740***	−8.612***
	(2.207)	(1.764)	(2.084)
ZPOVRATE	8.029***		
	(3.168)		
POPxPOV	1.892***		
	(0.739)		
ZGINI		4.511***	
		(1.021)	
POPxGINI		139.849**	
		(66.001)	
ZRATIO90_10			4.604
			(2.938)
POPxRATIO90_10			3.921**
			(1.587)
Adj R2	0.807	0.830	0.816
F	63.104	73.494	66.997

Note: All VIF values less than 2 except HHINC and ZPOVRATE in the Poverty Model where VIF values are 4.401 and 4.378.
Robust standard errors in parentheses.
***$p = 0.01$. **$p = 0.05$. *$p = 0.10$.

Discussion and conclusions

In many cities, economic inequality has risen to the top of the policy agenda. Part of our interest in reducing inequality rests in a fundamental belief that more equitable societies are more desirable (Madden, 2000; see also Montenegro, 2020). Further, "crime rates are higher in more unequal cities; people in unequal cities are more likely to say they are unhappy … [and] there is a negative association between local inequality and the growth of city-level income and population" (Glaeser et al., 2009:617). Relatedly, recent studies have found higher levels of economic inequality to be associated with lower assessments of subjective well-being (Kang and Rhee, 2021). As a practical matter, reducing urban inequality between poor and nonpoor, city and suburb, is also "good business" because it holds significant promise to enhance social welfare and generate benefits enjoyed throughout the metropolitan area.

TABLE 6 Regional models

	Base Model	Poverty Model	Gini Model	90/10 Model
Intercept	9.035	−4.661	39.411**	32.586*
	(24.634)	(27.453)	(18.338)	(19.314)
POP	5.326***	4.981***	2.889**	3.214**
	(1.913)	(1.794)	(1.427	(1.496)
HHINC	0.490***	0.748***	0.571***	0.554***
	(0.77)	(.233)	(0.064)	(0.068)
AMENITY	2.040*	2.297**	1.421	1.716*
	(1.094)	(1.086)	(1.047)	(1.025)
RTW	−1.548	−0.004	−1.995	−0.423
	(3.148)	(3.297)	(3.062)	(2.856)
ZPOVRATE		3.520		
		(3.409)		
ZGINI			3.747***	
			(1.043)	
ZRATIO90_10				3.946***
				(3.895)
MIDATL	−9.273***	−7.139	−6.702*	−5.374
	(4.391)	(4.623)	(3.661)	(2.703)
E.N.CENTRAL	−19.753***	−17.777***	−17.523***	−15.576***
	(3.136)	(3.125)	(2.304)	(2.930)
W.N.CENTRAL	−22.701***	−20.217***	−18.210***	−15.699***
	(3.625)	(3.747)	(2.815)	(4.227)
S. ATLANTIC	−16.648***	−15.666***	−14.234***	−12.850***
	(4.898)	(4.847)	(4.339)	(3.785)
E.S.CENTRAL	−19.455***	−19.274***	−19.019***	−17.940***
	(4.257)	(4.116)	(4.090)	(4.041)
W.S.CENTRAL	−21.566***	−23.283***	−21.379***	−20.523***
	(4.673)	(4.776)	(4.225)	(3.451)
MTN	−18.304***	−17.387***	−14.068***	−12.533***
	(4.046)	(3.828)	(3.316)	(3.134)
PACIFIC	−0.859	−2.880	0.839	1.705
	(4.407)	(4.634)	(3.312)	(1.076)
Adj R^2	0.847	0.860	0.880	0.884
F	42.034	42.935	51.215	53.280

Robust standard errors in parentheses.
Maximum VIF = 5.358 (S. ATL in 90/10 Model).
Reference region = New England.
****p* = 0.01. ***p* = 0.05. **p* = 0.10.

Realizing these benefits might not be a simple matter, however. From the Base Model it was revealed that the cost of living is somewhat inelastic with respect to changes in household income. On one hand, this is good news for those regions and households with high or growing income because income growth tends to outpace changes in the cost of living. On the other hand, because cost-of-living does not fully adjust downward, economic well-being in less prosperous regions can suffer when low or declining income is met with less-than-proportional changes in living costs. Thus, living costs associated with wage growth, especially in large "superstar" cities like Boston, San Francisco, and Seattle are likely to be shouldered by less mobile, lower income households especially if it is sufficiently strong to raise overall income per capita (Campbell and James, 2020).

That cost-of-living increases with increasing poverty and income inequality can also inform economic development policy. In the late 1970s, changes in the wage distribution started to favor those wage earners in the 90th percentile. At the same time, many cities began to lose middle-wage occupations due to production shifts and international trade (Abel and Deitz, 2019; Walden, 2019). The result was a "hollowing out" of regional economies and growing economic inequality within them. New occupations, though heavily concentrated in urban areas, are "highly polarized among skill categories" (Autor, 2019:32) suggesting bifurcated wage distributions and income inequality, within and between urban labor markets, that will persist for some time. Beyond the traditional goal of creating jobs and expanding tax base, a goal of today's economic development policy should include reducing economic inequalities. Rather than inducing top wage earners to leave, metropolitan areas can pursue development strategies aimed at building the wealth of those in the bottom half of the wage distribution by targeting and nurturing mid-level occupations and industries to fill production gaps in economic structure, lessen wage and income disparities while providing a pathway for lower- and moderately-skilled members of the workforce to enhance earnings and (hopefully) lower the incidence of poverty.

Strangely enough, the trend toward remote working arrangements associated with the COVID-19 pandemic might also impact metropolitan inequality. Although the long-term outlook for remote working is still unknown, some technology workers have left the high-cost urban areas of their employers in search of more space, lower living costs, and a higher quality of life (Florida and Ozimek, 2021). One result of skilled worker migration away from Boston, New York, Seattle, San Jose, and other high-cost areas has been rising vacancies, falling rents, and, perhaps, a small reduction in income disparities in these sending regions. Population growth in receiving metros like Fresno, CA, Boise, ID, or Greenville, SC, will exert upward pressure on living costs, but employment and wage growth in mid-wage occupations and sectors will likely follow. The aggregate impact of these trends is hard to gauge and not all workers can work remotely. Nonetheless, the prospect of a changing urban geography and its impact on economic well-being is intriguing.

Are less equal places more costly? Findings presented here indicate they are, and the results are robust with respect to variable choice and model specification. Whether through reductions in poverty or changes in the distribution of income whereby lower- and middle-wage earners receive an increasing share, the benefits of a more equitable distribution of resources will, through their impact on the cost of living, accrue to all residents of the metropolitan area.

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APPENDIX

TABLE A Descriptive statistics (untransformed data)

	Min	Mean	Median	Max	St. Dev
COLI	82.6	109.3	104.7	163.7	16.4
POP	637.519	2,357.927	1,266.078	19,276.644	2,811.452
HHINC	38.40	63.11	60.94	114.74	12.47
AMENITY	2.0	4.1	4.0	7.0	1.3
RTW	0.0	0.5	0.5	1.0	0.5
POVRATE	7.61	12.86	12.70	29.05	3.18
GINI	0.329	0.394	0.393	0.458	0.021
RATIO90_10	4.825	7.111	6.984	9.618	0.910

Note: Population and median household income in thousands. Descriptive statistics for POP, POVRATE, GINI, RATIO90_10 are for untransformed data.