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Driving to opportunity: Local rents, wages, commuting, and sub-metropolitan quality of life ☆

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ABSTRACT

We examine variation in local rents, wage levels, commuting costs, household characteristics, and amenities within metropolitan areas, for 2071 areas covering the United States, by density and central-city status. We demonstrate the sensibility of estimating wage levels by workplace, not residence, and recover decentralized rent gradients that fall with commuting costs. We construct and map a willingness-to-pay index, which indicates the quality of life typical households receive from local amenities when households are similar, mobile, and informed. This index varies considerably within metros, and is typically high in areas that are dense, suburban, sunny, mild, safe, entertaining, and have elevated school-funding.

1. Introduction

Households face many trade-offs when they decide where to live, as areas close to high-paying jobs or with desirable amenities are often expensive. Below, we consider how local wage levels, housing costs (or "rents"), and commuting costs vary both within and across metropolitan areas, using the most detailed level of geography in public-use Census files.[1] We then use these measures to construct a local willingness-to-pay index for a typical household based on how high housing and commuting costs are relative to available wages. Under strong conditions, such as household mobility and homogeneity, this index provides the value households place on local amenities, otherwise known as local "quality of life" (QOL).

Given how households are imperfectly mobile and heterogeneous, this one-dimensional quality-of-life index can only provide a limited perspective on the relative desirability of neighborhoods. The index is transparent and provides an economically intuitive complement to other measures of neighborhood quality or "livability" that abound in popular literature. It ranks beautiful areas along the Pacific the highest and areas rife with urban decay the lowest, lending the index plausibility. It is also positively correlated with various neighborhood amenities such as mild climate, safety, entertainment, and well-funded schools – typically thought of as desirable. While regression methods may be used with this index to try to value specific amenities, these methods are subject to potentially important omitted variable and simultaneity problems, such as household sorting. Indeed, the residents of a neighborhood will not only influence the amenities it provides, but may also be considered an amenity themselves.

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[1] We often allude to "housing costs" which are either a rent or an imputed rent for housing. We find it important to distinguish land rents from housing rents because construction costs may vary across metro areas.

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Although this work focuses on constructing a single index of neighborhood quality, its elements are pertinent to more complex analyses of hedonic markets and household sorting, e.g. Bajari and Kahn (2005), Yinger (2014), which measure willingness-to-pay through rents alone. Our index makes it easier to compare neighborhoods across metropolitan areas. In particular, we make several adjustments beyond the last similar study of sub-metropolitan quality of life by Blomquist et al. (1988). First, following Albouy (2008) – who estimates willingness-to-pay across metro areas – we down-weight the benefit of wage levels to account for federal taxes, and up-weight rent levels to account for unobserved non-housing costs. Second, we add commuting costs to rents to provide a fuller measure of the "urban costs" faced by households. Third, we estimate local wage levels by place of work, rather than place of residence, to mitigate potential biases from unobserved skills. Fourth, we cover the entire United States, including non-metro areas, and areas within counties whenever possible.

To complement and contextualize the analysis on willingness to pay, we also describe patterns in local rents, wages, and commuting costs, as well as household characteristics and observable amenities. These patterns involve variation within and across metros, between suburbs and central cities, and across communities of varying densities. Using regression methods, we distinguish how much raw variation in wages, rents, and commutes are explained by the observed characteristics of workers or housing units, as opposed to the locations themselves. We find that rent and wage-predicting characteristics vary more strongly within metros than across them, indicating stronger household sorting. Meanwhile, rent and (especially) wage levels due to location vary much more across metro areas than within. Controlling for local wages, rents fall with commutes in a manner consistent with standard theories of rent gradients.

Section 2 motivates our analysis in the context of existing research on local amenities and commuting. We synthesize relevant theories in Section 3 to provide the basis for the quality-of-life index. Section 4 describes the data at the Public Use Microdata Area, or "PUMA," level of geography. We present our measure of quality of life in Section 5 using maps for the continental United States, as well as New York, San Francisco, Detroit, and Atlanta. These maps reveal as much disparity in willingness-to-pay within Manhattan as across the most and least desirable states. In Section 6, we document how a few amenities *predict* much of the variation in quality of life, and how their estimated values are consistent with existing research, while being subject to numerous caveats and limitations.

2. Motivation and related literature

Our methodology combines insights from two lines of research on how local wages and rents are determined: the first on local amenities, the second on commuting. Beginning with Oates (1969), the empirical literature on amenities (including local public services) builds off of the theory of Tiebout (1956) by assuming that workers are mobile, have access to the same labor market, and that commutes can be ignored or controlled for. In this framework, amenities may be valued by examining how they co-vary with rents inside a metro area, holding other factors constant.

Rosen (1979) adapts this framework to examine amenity differences across metro areas with separate labor markets, arguing that low wages as well as high rents signal amenity values. He and his student, Roback (1982), use several measures of individual amenities as independent variables in wage and rent regressions. The quality-of-life index is then given by the annualized difference in rents to wages predicted by those amenities. One concern with such an index is that it is sensitive to which amenities the researcher considers relevant.[2] Gabriel et al. (2003) factor in non-housing costs-of-living in addition to rents, albeit only at the state level. Not taking a stand on what amenities belong in the quality-of-life index, Beeson and Eberts (1989), Gabriel and Rosenthal (2004), and Chen and Rosenthal (2008) construct indices at the metro level based on how high wages are compared to rents, controlling only for worker and housing characteristics. This "agnostic" index implicitly includes the value of observed and unobserved amenities together.[3] Albouy (2008) incorporates federal taxes and missing non-housing costs into a similar index to infer that willingness-to-pay in high-rent, high-wage (typically large) metro areas is much higher than previous research implied. He regresses the agnostic quality-of-life index in a second-stage regression to infer how much quality of life is predicted by observed amenities.[4] We use a similar methodology, refining it for sub-metropolitan analysis.

Most recent estimates of individual amenity values follow a more quasi-experimental or structural approach. The quasi-experimental approach helps to eliminate problems with unobserved variables, but may still be confounded by household sorting behavior.[5] Furthermore, quasi-experiments are unavailable for many amenities making this approach too limited to provide an overall index of neighborhood desirability. Structural approaches offer a wealth of methods to account for household sorting according to preferences and income, as well as how this sorting may generate local amenities, such as the provision of local public goods. Despite their strengths and flexibility, these models often require strong parametric identifying assumptions and computationally-intensive estimation procedures which make their validity difficult to assess.[6]

Research on how commuting impacts local prices is focused on intra-urban gradients. Alonso (1964), Mills (1967), and Muth (1969) predict rent gradients that fall with distance to a central business district, as lower rents compensate households for higher commuting costs. Hoehn et al. (1987) consider how a *city-wide*

[2] A more artificial approach is seen in various popular scores of quality of life, often termed "livability." Detailed scores, often at the neighborhood level, are available on websites such as Areavibes.com and Streetadvisor.com. Nate Silver (2010), of election polling fame, provides quality-of-life rankings for neighborhoods in New York City. Streetadvisor.com relies on crowd-sourced user reviews for streets, neighborhoods, and cities. Areavibes.com and Silver (2010) apply weighting algorithms to various observable amenities. For further details see Appendix E.

[3] Beyond amenity indices, the essential insight of equal indirect utility across areas has also been used by McDuff (2011) to predict migration flows and Kim et al. (2009) to explain intra-city wage differentials.

[4] A recent unpublished working paper by Bieri et al. (2013) performs an analysis similar to Blomquist et al. (1988) at the county-level. They incorporate many of the features new in Albouy (2008) regarding taxes and non-housing costs, and correct for selection from inter-state migration using techniques adapted from Dahl (2002). While they find the Dahl correction important, we find it to be negligible, perhaps as we used a larger set of worker controls in our wage equation. Bieri et al. use a set of amenities larger than any similar study to determine relative amenity expenditures. Since many amenities as well as worker and housing characteristics remain unobserved, this technique does not guarantee reduced omitted variable bias. We prefer to use a more agnostic quality-of-life measure and explore how it is *predicted* by a parsimonious set of amenities.

[5] For examples, see Davis (2004) for health, Chay and Greenstone (2005) for air quality, and Cellini et al. (2010) for school facilities. Crime has also been valued using housing prices, see Linden and Rockoff (2008), Pope (2008), or Gautier et al. (2009). Crime has even been examined as a cause of misallocation of time at work, see Hamermesh (1999). Over time, residents may re-sort across neighborhoods, causing issues with the estimates, see Kuminoff and Pope (2013) and Banzhaf (2013). Studies that use spatial discontinuities, such as district borders (Black, 1999), may be subject to sorting effects (Bayer et al., 2007). Many amenities, like climate or geography, change over long time frames, and so it is sensible to model sorting explicitly. Albouy et al. Albouy (2008) do just that using the QOL measures here with the method of Bajari and Benkard (2005) to examine climate amenities.

[6] See Kuminoff et al. (2013) for a review of this literature. Notable examples include Epple and Sieg (1999) on levels of school funding, and Bayer and Timmins (2005) on equilibrium properties of sorting models. Angrist and Pischke (2010) and Nevo and Whinston (2010) provide debate on the pros and cons of structural modeling and credible inference.

amenity affects wages and prices in a monocentric city, and conclude "the amenity valuation results of Roback's pure inter-regional case carry over." Muth (1969), White (1976) and Straszheim (1984) theorize that wages should fall with distance from urban centers and sub-centers as workers accept lower wages for shorter commutes.[7]

Empirical evidence on wage gradients (e.g. Eberts, 1981; Madden, 1985; Zax, 1991; McMillen and Singell, 1992) often supports the above hypothesis. Evidence on rent gradients is more mixed (e.g. Dubin and Sung, 1987), at least over short distances, suggesting the importance of confounding amenities. A stark example is metro Detroit, where central-city land is often cheaper and less developed than suburban land, and much employment is decentralized. Gabriel and Rosenthal (1996) provide a more decentralized theory, similar to ours, but use it to address the spatial mismatch of employment for minorities.[8] Busso et al. (2013) demonstrate the practical importance of examining commuting behavior and sub-metropolitan wage levels when examining the impact of the federal urban Empowerment Zone program.

Estimates of local wage and rent levels may be biased by unobserved worker skills or housing quality. Fu and Ross (2013) estimate a positive effect of employment density on wages that is unaffected by detailed controls for place of residence, but is rendered insignificant when commuting is controlled for. This provides evidence that workers' unobserved earnings abilities are unrelated with where they work, even if they are related to where they live.

3. A model of residential choice with commuting

3.1. Household preferences and constraints

We incorporate commuting into Rosen's (1979) model, expanded by Albouy (2008). Households are homogeneous, mobile, and have information about each community. They consume a traded good, x, with price normalized to one, a non-traded home good, y, with price (or rent) p, leisure time, l, commuting time, f, and a vector of amenities, $\mathbf{Z}$. For simplicity, we aggregate amenities into a single index, $Q = \tilde{Q}(\mathbf{Z})$. Household preferences are modeled by a utility function, $U(x, y, l, f; Q)$, which is quasi-concave and decreasing in f and increasing in x, y, l, and Q.[9]

Households choose their place of residence, j, which differ in local prices, p^j, and quality of life, Q^j. They also choose their hours, h, and place of work, k, which differ in wages, w^k. Commuting between home and work takes time f^{jk}, and is assumed to have a proportional monetary cost, $c \cdot f^{jk}$, where $c \geqslant 0$ is a constant. Households receive income from wages, $w^k h$, plus non-labor income, I, from a diversified portfolio of land and capital. They pay federal taxes $\tau(w^j h + I)$, which are rebated lump-sum. State taxes and tax benefits to owner-occupied housing are modeled in Appendix C.[10] The resulting household budget constraint is then $x + p^j y + cf^{jk} \leqslant w^j h + I - \tau(w^j h + I)$. The time endowment is normalized to one, so that households satisfy the time constraint $h + l + f^{jk} \leq 1$. The following expenditure function joins the utility function and two constraints to express the after-tax net expenditure necessary for a household to obtain utility u:

$$e(p^j, w^k, f^{jk}; Q^j, u) = \min_{x,y,h,l}\{x + p^j y - w^j h - I + cf^{jk} + \tau(w^j h + I)$$
$$: U(x, y, l, f^{jk}; Q^j) \geqslant u,\ h + l + f^{jk} \leq 1\}.$$

This function, assumed to be continuously differentiable, increases in the urban-cost parameters p^j and f^{jk} and decreases in the local opportunity parameters w^k and Q^j, meaning $\partial e/\partial p, \partial e/\partial f \geqslant 0$ and $\partial e/\partial w, \partial e/\partial Q \leqslant 0$.

3.2. Equilibrium in places of residence and work

Mobile and informed households do not choose a place-of-residence and place-of-work combination (j, k) less satisfying than any other. When households are homogeneous, all observed combinations (j, k) must provide the same level of utility, u. This equilibrium can be characterized neatly with the expenditure function:

$$e(p^j, w^k, f^{jk}; Q^j, u) = 0, \tag{1}$$

for all (j, k) combinations in the data. No one, on net, needs to be paid extra for where they live and work; everyone is equally satisfied with the conditions they face.

To characterize differences in prices and wages, we implicitly differentiate condition (1). By varying the place of residence, j, we find

$$\frac{\partial e}{\partial p} dp^j + \frac{\partial e}{\partial f} df^j + \frac{\partial e}{\partial Q} dQ^j = 0, \tag{2}$$

should hold for all observed residences and commutes. With some abuse of notation, df^j denotes the change in commuting time by varying residences. This expression generalizes the rent gradient: higher rents may be associated with lower commute times or higher quality of life.

The urban-wage gradient is expressed by varying the place of work, k, requiring that

$$\frac{\partial e}{\partial w} dw^k + \frac{\partial e}{\partial f} df^k = 0, \tag{3}$$

across all observed commutes and workplaces. Here, df^k is the change in commuting time by varying workplaces. Workers will travel longer if they are compensated with higher wages.

The model so far is similar to that on rent and wage gradients (e.g. McMillen and Singell, 1992) with amenities added in. The goal here is not to test whether these gradients hold. Instead, we combine (2) and (3) to infer a local willingness-to-pay measure for changes in quality of life, dQ^j. This yields the expression $-(\partial e/\partial Q)dQ^j = (\partial e/\partial p)dp^j + (\partial e/\partial w)dw^k + (\partial e/\partial f)df^{jk}$ where

[7] Turnbull (1992) examines the role of leisure in a related model and concludes that it matters little for examining wage gradients. "The introduction of leisure choice into the local employment location model does not alter either the form of the location equilibrium location condition or the immediate implication for the wage rate-distance relationship." This occurs since households put the same value on work and leisure on the margin.

[8] While racial segregation is of obvious importance, we defer most questions on race to existing and future research. When we do examine worker heterogeneity, we focus on a single-index that aggregates observable characteristics such race, age, education, and immigrant status according to how these factors impact wages.

[9] Note that the amenities of a location j may be physically located in adjoining areas, such as museums within the metro area. By aggregating the amenities we impose that preferences for consumption goods and amenities are weakly separable, which is unlikely to hold. Some amenities, such as beaches, may be closer substitutes to leisure than others. Colwell et al. (2002) considers how amenities may impact behavior with varying commutes. In such cases, the utility function would need to incorporate multiple Q or Z arguments. In practice, these concerns could have a second-order importance on QOL estimates that our measures ignore. For instance, in high amenity areas, residents may work less at their market job, and thus put less importance on local wages.

[10] We do not model savings behavior explicitly, as the portfolio or return to savings do not depend on where people live. A degree of household wealth is tied up in home equity, but with perfect capital markets, this will not matter. In real life, homeowners in more expensive areas may have greater equity (or leverage) in local land, but the rate of return on risk-adjusted savings should be the same. In a dynamic setting, it could be interesting to look at income effects from windfall capital gains in local land markets. This would then require us to distinguish individuals from where they used to reside to where they currently do. We save this complex issue for future research.

$df^{jk} \equiv df^j + df^k$ is the total difference in time spent commuting. We apply the envelope theorem (i.e. Shepard's Lemma) to the expenditure function (1) to interpret the derivatives, which we evaluate at the national average. Accordingly, $\partial e/\partial p = \bar{y}$ is average housing consumption, $\partial e/\partial w = -(1-\tau')\bar{h}$, average labor supply net of taxes, and $\partial e/\partial f = [c + (1-\tau')\bar{w} - \alpha]$, the sum of monetary and after-tax opportunity cost of working net of the "leisure-value" of commuting, $\alpha \equiv (\partial U/\partial f)/(\partial U/\partial x)$. Combining these, we solve for the marginal willingness-to-pay for local quality of life in terms of local rents relative to wages, adjusted for commuting:

$$p_Q dQ^j = \bar{y} \cdot dp^j - (1-\tau')\bar{h} \cdot dw^k + [c + (1-\tau')\bar{w} - \alpha]df^{jk}, \tag{4}$$

where $p_Q \equiv \partial e/\partial Q$ is the marginal valuation of Q.[11] If wages are rearranged on the left, the expression relates how higher urban costs, $\bar{y} \cdot dp^j + [c + (1-\tau)\bar{w} - \alpha]df^{jk}$ are paid to access residential amenity opportunities, $p_Q dQ^j$, or employment opportunities, $(1-\tau')\bar{h} \cdot dw^k$.[12] Alternatively, high wages compensate workers for high urban costs or low amenities.

3.3. Applying and parametrizing the model

To operationalize the model, we divide (4) by average income $\bar{m}$, re-express the level-differentials in terms of log-differentials $\hat{p}^j \equiv dp^j/\bar{p}, \hat{w}^k \equiv dw^k/\bar{w}, \hat{f}^{jk} \equiv df^{jk}/\bar{f}$, and replace the coefficients with share parameters. The marginal willingness-to-pay for local amenities, expressed as a fraction of income, $\hat{Q} \equiv p_Q dQ^j/\bar{m}$, is then

$$\hat{Q}^j = s_y \hat{p}^j - (1-\tau')s_w \hat{w}^k + \underbrace{\left[s_c + (1-\tau')s_w \frac{\bar{f}}{\bar{h}} - \alpha \frac{\bar{f}}{\bar{m}}\right]\hat{f}^{jk}}_{\hat{c}^{jk}}, \tag{5}$$

where $s_y = \bar{p}\bar{y}/\bar{m}$ is the expenditure share for home goods, $s_w \equiv \bar{w}\bar{h}/\bar{m}$ is the income share from labor, $s_c \equiv c\bar{f}/\bar{m}$ is share of income spent on commuting, and $\bar{f}/\bar{h}$ is the ratio of time spent commuting to time spent working. The last term on the right, $\hat{c}^{jk}$, is the "commuting-cost differential," which measures the full cost of commuting as a fraction of gross income.

For the non-commuting parameters, we follow Albouy (2008). $s_w = 0.75$ allows for 25% of income to come from non-labor sources. $s_y = 0.361$ accounts for typical expenditures on housing (22%) plus the costs of non-housing goods, which are strongly related to rents, by raising the share another 14 percentage points. Marginal tax rates, τ, are based on average marginal income tax rates, a portion of payroll tax rates, and state taxes insofar as wages vary within states. Tax advantages for owner-occupied housing are also accounted for.[13]

For the commuting parameters, we use information from the Survey of Income and Program Participation (SIPP) and National Highway Summary of Travel Trends. We take the median percent of income spent on commuting by mode: $s_c = 0.049$ for drivers, $s_c = 0.033$ for transit-users, and $s_c = 0.00$ for walkers. To determine time costs, we calculate that the average worker in 2000 worked 1822 hours and spent 184 hours commuting (U.S. Census), roughly 10% of the working day, and thus $\bar{f}/\bar{h} = 0.10$.[14]

The greatest uncertainty involves the parameter α: marginal commuting time is valued as work time if it equals zero and as leisure time if it equals the after tax wage, $(1-\tau')\bar{w}$. Studies have suggested a range of values for this parameter, although we find the value of $\alpha = 0$ to be the most plausible and straightforward. This value is supported by evidence from Small et al. (2005), from stated and revealed preference, and Fu and Ross (2013), from wage gradients, that commuting is not preferred to working. Well-being data from Kahneman and Krueger (2006) find that subjective affect while commuting is as low or lower than while working, reinforcing this value. Alternative values of α may be accounted for easily.

3.4. Strengths and limitations of the model

The quality-of-life index proposed in (5) is based on a straightforward integration of standard urban theories. The chosen parametrization of willingness-to-pay applies only to a typical household. Particular households will vary in how they value wages relative to housing and commuting costs. Households with fewer or no earners, such as retirees, place less value on wages; households with children may value housing costs more. Implicit marginal tax rates in taxes and transfers can also vary. It is straightforward to parametrize the model differently to account for such forms of heterogeneity.[15]

While free mobility is a standard assumption, in reality, households do not move unless the benefit merits the cost of moving. Declining areas tend to keep households with greater moving costs, and thus may have inflated measures of willingness-to-pay.

Households may vary considerably in their tastes for local amenities, such as schools or climate. Nevertheless, some evidence does point to substantial similarity in preferences. Pew Research Center (2009) finds that individuals of different ages, gender, income, and education often state similar preferences for which metro areas they find most livable.[16] Research on taste heterogeneity using generally assumes that different groups pay the same rent. Instead, it relies on differences in relative population frequencies to infer differences in tastes (e.g. Bayer et al., 2007). While there is much evidence of sorting by race and income across neighborhoods (e.g. Cutler and Glaeser, 1997; Ioannides, 2004), converting relative frequencies into willingness-to-pay measures relies on strong parametric assumptions.

With heterogeneous preferences, the supply and demand of amenities matters. For example, the marginal bid for land on the coast should rise if the supply of coastline per person falls. Although typical households may value car-friendly suburban developments, if these are abundant relative to walkable downtowns, the latter may be costlier, as downtown residences are allocated only to the highest bidders (Gyourko et al., 2013).

Tastes for different areas may depend considerably on the local population either directly or indirectly for the "artificial" amenities they bring. Yinger (2014) finds considerable differences in demand for neighborhood ethnic composition. Boustan (2013) estimates

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11 Since Q does not have natural units, neither p_Q nor dQ^j alone have operational meaning, although their product does as $p_Q dQ^j$ is the marginal willingness-to-pay to enjoy the amenities in location j. Although the approximation sets p_Q at the national average, the price of amenities may change across locations.

12 Timothy and Wheaton (2001) consider the situation when wages, w^k, are fixed and exogenous. Then, only in knife-edge cases will households commute from the same place of residence to more than one work place. With endogenous wages, wages in further (closer) places may rise (fall) to allow for more varied commuting behavior, as we see in the data. Moreover, in a more realistic model, workers may vary in their transportation costs, preferences of location, or receive idiosyncratic wage offers from different locations, each with mean w^k, all of which could cause workers from the same residences to commute to a large variety of workplaces. For an example of such a model which allows for income heterogeneity, see Gabriel and Rosenthal (1996).

13 In Appendix C.2 we explain how we adjust marginal rates by state as well as deductions for housing.

14 Annual commuting time is the product of 418 commuting trips, averaging 26.4 min each way. Commute time is assumed to be equal by mode.

15 The quality-of-life index is also moderately robust to behavioral responses in leisure or consumption due to differences in rents, wages, or commuting costs – because of the envelope theorem, such considerations have only a second-order effect.

16 For those making less than \$30,000 a year, 13% state they would live in Detroit, 30% in San Francisco. For those making over \$100,000, the rates are 7% for Detroit and 48% for San Francisco. The differences for most other cities, like Atlanta (24% and 26%) and New York (21% and 35%), are smaller, and there are very few cases of inversion.

high demand for high-income neighbors, as they provide high-quality schools relative to property tax rates. Ultimately, neighborhood "quality" is a sensitive topic that depends on many subjective factors.

As an example, consider a housing project built for low-income households in a low-wage area, such as Decatur, IL. Even if subsidized residents prefer Decatur to their previous location, say Chicago, they should still have a lower willingness-to-pay than previous residents, who paid full price to be there. As the proportion of low-income households increases, the local per-capita tax base may decline, causing public services to fall. Unless original residents prefer the new mix of residents to the old, or the change in local amenities it brings, the introduction of public housing is likely to reduce local willingness-to-pay. These issues remain open empirical questions.[17]

As another example, consider the impact of zoning restrictions meant to exclude low-income households. If such zoning is binding, low-income households will have a limited supply of neighborhoods to choose from, say in the central city. These limits may lengthen commuting times and raise rents in those neighborhoods, artificially increasing measured willingness-to-pay. If low-income households live in less desirable neighborhoods, zoning would attenuate the quality-of-life differences we infer. The resulting segregation of rich from poor could also reinforce differences in artificially produced amenities.

4. Wage, rent, and commuting-cost estimates

4.1. Units of geography

We estimate wage, rent, and commuting-cost differentials from the 5% sample of the U.S. Census in the Integrated Public Use Microdata Series (IPUMS) for 2000 (Ruggles et al., 2004).[18] The public-use files identify households' location of residence down to 2071 Public Use Microdata Areas. These areas have an average population of 135,887, and a minimum of 100,000. The Census Bureau does not provide names for 2000 PUMAs; we name them using the counties, municipalities, or neighborhoods they contain.

The geographic detail of the PUMAs increases with population density. 186 PUMAs correspond exactly to counties. 1266 PUMAs are entirely contained within a subset of 288 counties, and are often identifiable neighborhoods or municipalities. For example, in Washtenaw County, MI, one PUMA corresponds to the city of Ann Arbor while the other refers to areas in Washtenaw County outside Ann Arbor. In the borough of Manhattan (New York County, NY), the PUMAs correspond to sub-boroughs, such as the Upper East Side. 2654 counties are entirely contained within one of 526 larger PUMAs. For example, Clarke, Madison, and Occonee counties in Georgia form a single PUMA around Athens, GA.

We aggregate our PUMA level estimates up to the level of Metropolitan Area, as defined by the Office of Management and Budget (2000). These 276 Metropolitan Statistical Areas (MSAs) are supersets of counties – such as the MSA for Athens, GA which coincides with the three counties listed above. 19 of the largest MSAs are categorized as Consolidated MSAs (CMSAs) which are in turn made up of 55 Primary MSAs (PMSAs). Thus, from 2071 PUMAs we may assemble the data into 3081 counties, 276 MSA/CMSAs, and 331 MSA/PMSAs (splitting the 19 CMSAs into 55 PMSAs).[19]

Within metro areas, the Census designates some places as *central cities*, typically the largest population and employment centers. We separate these from other places within MSAs, which we label *suburban*; places completely outside of MSAs are *non-metropolitan*.[20] We also classify areas according to residential population density – calculated at the census-tract level and averaged by population – using cut-offs of 1000 and 5000 residents per square mile.

Panel 1 of Table 1 presents means of the estimated differentials and related statistics for central city, suburban, and non-metro areas. The rent, wage, and commuting-cost differentials are mapped in Fig. 1A–C. Panel 2 presents this information summarized by the location's average density. Panel 3 presents the standard deviations of the differentials across the United States, and decomposes the variance within and across metro areas. In Table 2, these statistics are presented for PUMAs in two well-known counties: New York, NY (Manhattan), and San Francisco, CA. Table 3 contains the differential measures for various levels geography in 5 MSAs; Table A1 in the Appendix contains them for all 2071 PUMAs.

4.2. Housing costs due to location and composition

We use both housing values and gross rents, including utilities, to calculate rent, or "housing-cost," differences. To impute owned housing rents, and make them comparable to gross rents for rental units, we multiply housing values by a rate of 7.85% (Peiser and Smith, 1985) and add utility costs. We regress rents on place-of-residence indicators, μ_p^j, and controls for housing composition, denoted X_{pi}^j – i.e., size, rooms, acreage, commercial use, kitchen and plumbing facilities, type and age of building – each interacted with renter status.[21] The resulting regression equation is

$$\ln p_i^j = X_{pi}^j \beta_p + \mu_p^j + \varepsilon_{pi}^j, \tag{6}$$

where estimates of μ_p^j are the rent differentials, $\hat{p}^j$, for location j. Remaining differences in mean housing costs, $\overline{\ln p^j} - \mu_p = \bar{X}_p^j \beta^j$, are attributed to mean differences in observable housing composition across areas, $\bar{X}_p^j$, which we call "housing quality." Since X involves measures like the number of rooms, "quality" also refers to quantity of housing. We also include corrections for rent control for New York City and San Francisco.[22]

[17] Diamond and McQuade (2015) estimate how different households value new construction from the Low Income Housing Tax Credit Program.

[18] We acknowledge that the quality-of-life estimates are slightly dated. Nevertheless, the 2000 Census offers the last 5% snapshot of the U.S. More recent data on housing prices may not be driven by market fundamentals due to the wake of the boom and bust cycle, as detailed in Ferreira and Gyourko (2011). Furthermore, recent evidence in Lee and Lin (2013) highlights remarkable persistence in the desirability of most neighborhoods, especially in areas with natural amenities.

[19] PUMAs can usually be assigned uniquely to counties or MSAs, but in cases where they overlap MSA (or county) boundaries, the observations are subdivided and given a fractional weight according to the proportion of the population that resides in each area. All of our aggregations use population-weighted averages of these PUMA values.

[20] For instance, all of New York City, Bridgeport, Newark, and New Haven are deemed central city, but none of Long Island is. The cities of San Francisco, Oakland, San Jose, Berkeley, and Richmond are all central city, but Fremont, Hayward, Union City, and all of Marin and San Mateo counties are not.

[21] We combine rent and imputed-rent measures to avoid potential problems created by local differences in home-ownership (see Table A2). For instance, in Manhattan 80% of housing units are rented, whereas in King William Co., VA, only 13% are rented. Using more recent data, Albouy and Hanson (2014) calculate an average user cost for owner-occupied housing of 6.2%. With our controls for tenure status, the rate used has only a minor effect.

[22] Pollakowski (2003) estimates that in the lower 6 sub-boroughs of Manhattan, prices for rent-controlled units would be 37% higher without rent control. Using a similar method with Census data, we determine that prices for rent-controlled units in San Francisco would be 22% higher in the absence of rent control. To correct for this, we add the fraction of rent-controlled units in each PUMA times $\ln(1+a)$ to the housing cost index, where a is how much prices for units would appreciate in the absence of rent control.

Table 1
Rent, wage, commuting-cost, and quality-of-life differentials across the U.S., 2000.

Differential	Population	Rents/hous. cost		Wage			Commuting		Quality of life	
		Location index or "Rent"	Composition or "Quality"	Index by workplace	Index by residence	Composition or "Skill"	Index of full cost	Time diff. only	Workpla. adj. index	Simple (not used)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Central city, suburban, or non-metropolitan area										
Central city (in metro)	85,401,116	0.070	−0.099	0.033	0.012	−0.044	−0.003	−0.007	0.004	0.016
Suburban (in metro)	141,255,868	0.088	0.050	0.034	0.053	0.035	0.006	0.058	0.019	0.004
Non-metropolitan areas	54,764,922	−0.335	0.026	−0.140	−0.156	−0.020	−0.012	−0.139	−0.054	−0.035
Panel B: By residential population density										
>5000 per square mile	75,957,757	0.276	−0.138	0.110	0.087	−0.061	0.006	0.109	0.043	0.047
1000–5000 per square mile	126,073,690	0.010	0.051	0.004	0.022	0.040	−0.001	−0.026	0.001	−0.006
<1000 per square mile	79,390,459	−0.280	0.051	−0.111	−0.117	−0.005	−0.005	−0.063	−0.043	−0.035
Panel C: Standard deviations										
All PUMAs		0.358	0.140	0.128	0.145	0.105	0.018	0.220	0.079	0.066
Across metropolitan areas		0.310	0.066	0.123	0.130	0.047	0.014	0.176	0.060	0.052
Within metropolitan areas		0.179	0.123	0.033	0.065	0.093	0.011	0.132	0.050	0.041
Fraction of variance within		*0.250*	*0.772*	*0.066*	*0.201*	*0.784*	*0.373*	*0.360*	*0.401*	*0.386*

In Panels A and B, the population numbers in column 1 are totals, while the rest are averages. Wage, housing price, and commuting data are taken from the U.S. Census 2000 IPUMS for 2071 Public-Use Microdata Areas (PUMAs). Differentials are relative to the national average. Housing-cost differentials are based on the average logarithm of gross rents or housing prices plus utilities, with the cost-index determined by the indicator for what PUMA it is located in, and the composition index by the predicted value based on other observable housing characteristics. Wage differentials are based on the average logarithm of hourly wages for full-time workers ages 25–55, with the "By workplace" differential estimated off of work-place indicators, averaged over resident workers, the "By Residence" estimated off of residential indicators, and the "Composition" index by the wage predicted by observable characteristics. Commuting-cost differentials for workers are estimated from monetary-cost and time–cost differentials explained in the text, the latter based on time to work. The adjusted quality-of-life index is estimated from the housing-cost, workplace-wage, and commuting-cost indices in columns 2, 3, and 7, according to Eq. (5), as calibrated in the text, while the simple index is estimated from the housing-cost and residence-wage indices, only. In Panel C, non-metropolitan areas of each state are treated like distinct metropolitan areas, although the results do not change substantially if they are excluded. See text for greater detail.

Our estimates may be contaminated by differences in unobserved housing quality not captured by Census-provided variables. For example, two-bedroom apartments built in a 1960s-era Chicago suburb are likely to be more spacious than similar ones built contemporaneously in the Chicago Loop. Biases in rent differentials bias quality-of-life estimates in the same direction. Thus, high "quality of life" may reflect high unobserved housing quality. If *unobserved* housing quality is biasing the rent estimates, it seems likely that rent estimates would be correlated with measures of *observed* housing quality. As shown in Appendix Fig. A, the correlation between the two is almost zero, suggesting that unobserved housing quality is not systematically correlated with willingness-to-pay for local amenities.[23]

Fig. 1A maps the rent index across the United States. Appendix Table A2 summarizes the index and details the variables. In Table 1, we see rents are 2% higher, on average, in the suburbs than in central cities. This fact runs contrary to standard rent-gradient predictions, although the maps reveal that rents do eventually fall away from city centers. Outside of metro areas, rents are 35% (42 log points) lower than in suburbs. Panel B reveals that dense areas have the highest rents, as predicted by standard urban models.

In column 3, we see that housing quality in central cities worth 14% less than in the suburbs. Quality also falls by about 10% each time between high and medium, and medium and low density areas. This is the case as units in denser, central areas are older and smaller.

Panel C provides evidence that rent differences due to housing quality are considerable, but smaller than differences due to location. In addition, rent levels (due to location) vary more across metro areas than within them, while the opposite is true of housing quality.

4.3. Wage levels estimated by residence and workplace

To calculate wage differentials, $\hat{w}^k$, we use hourly wages from a sample of workers, ages 25 to 55, who worked at least 30 hours a week and 26 weeks a year. We regress log wages on place-of-work indicators, μ_w^k, and controls for worker composition, or skills, X_{wi}^k – i.e., education, experience, race, occupation, industry, and veteran, marital, and immigrant status – each interacted with gender. The regression equation is

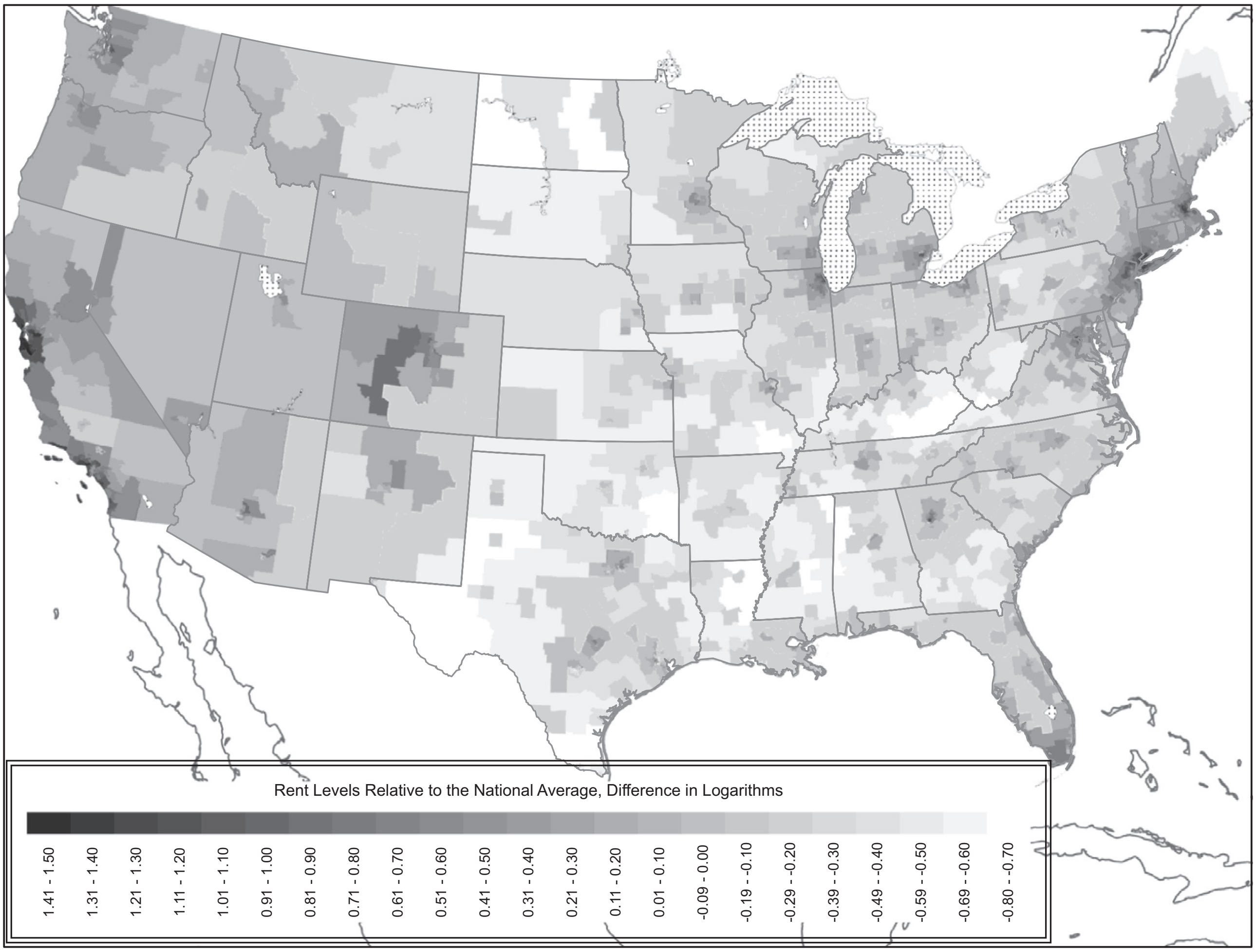
$$\ln w_i^k = X_{wi}^k \beta + \mu_w^k + \varepsilon_{wi}^k. \tag{7}$$

We calculate wage differentials for residents in location j by averaging μ_w^k, according to the proportion of residents of j who work in each place k. This is interpreted as the measure of the wage opportunities, $\hat{w}^k$, available to residents, when they incur the commuting costs estimated below. We map the wage index in Fig. 1B. The appendix summarizes related worker measures (Table A3), and details the variables. We also estimate differences in wages due to average differences in observed characteristics or "skills,' $\bar{X}_w^k$, weighting them by their estimated return, $\hat{\beta}$.

In column 6 of Table 1 we see notable variation in observed skills: workers' predicted wages are 4% below average in central cities, and 4% above average in suburbs.[24] Observed skills are also 6% lower in high-density areas, and 4% higher in medium-density areas. The typical standard deviation is 10 log points, with most of the variation within metro areas. This highlights the importance of income-sorting at the sub-metropolitan level.

[23] For instance, housing quality is very high in parts of suburban Atlanta (e.g. Alpharetta), although the location is quite average. Meanwhile, the housing quality is quite low where the locational rent is high, such as in Hawaii, Manhattan, and the San Francisco Bay Area. Within Manhattan, units in lower cost Harlem have a higher housing quality than units in Midtown, Downtown, or the Upper East and West Sides. For homes of the very wealthy, possible biases are mitigated by the fact that housing values are censored at $1 million. When density is flexibly controlled for, a one-point increase in housing-cost predicts a 0.1 point increase in the value of housing composition. Nevertheless, Malpezzi et al. (1998) determine that rent indices derived from the Census using hedonic methods perform as well as most other indices.

[24] This fact is consistent with standard urban sorting models when the income elasticity for housing is higher than that for the costs of commuting.



(A)

Fig. 1. (A) Residential rents (gross or imputed) across the United States, 2000. (B) Wage levels by workplace across the United States, 2000. (C) Commuting costs across the United States, 2000.

The evidence of sorting on *observed* skills raises concerns about *unobserved* skills. This problem may be mitigated within metros, by measuring wage opportunities by place of work. This depends on evidence in Fu and Ross (2013) that workers do not sort across workplaces according to their unobserved skills.[25] Fig. 2 graphs wage estimates by place of work against those by residence; the former vary less than the latter.

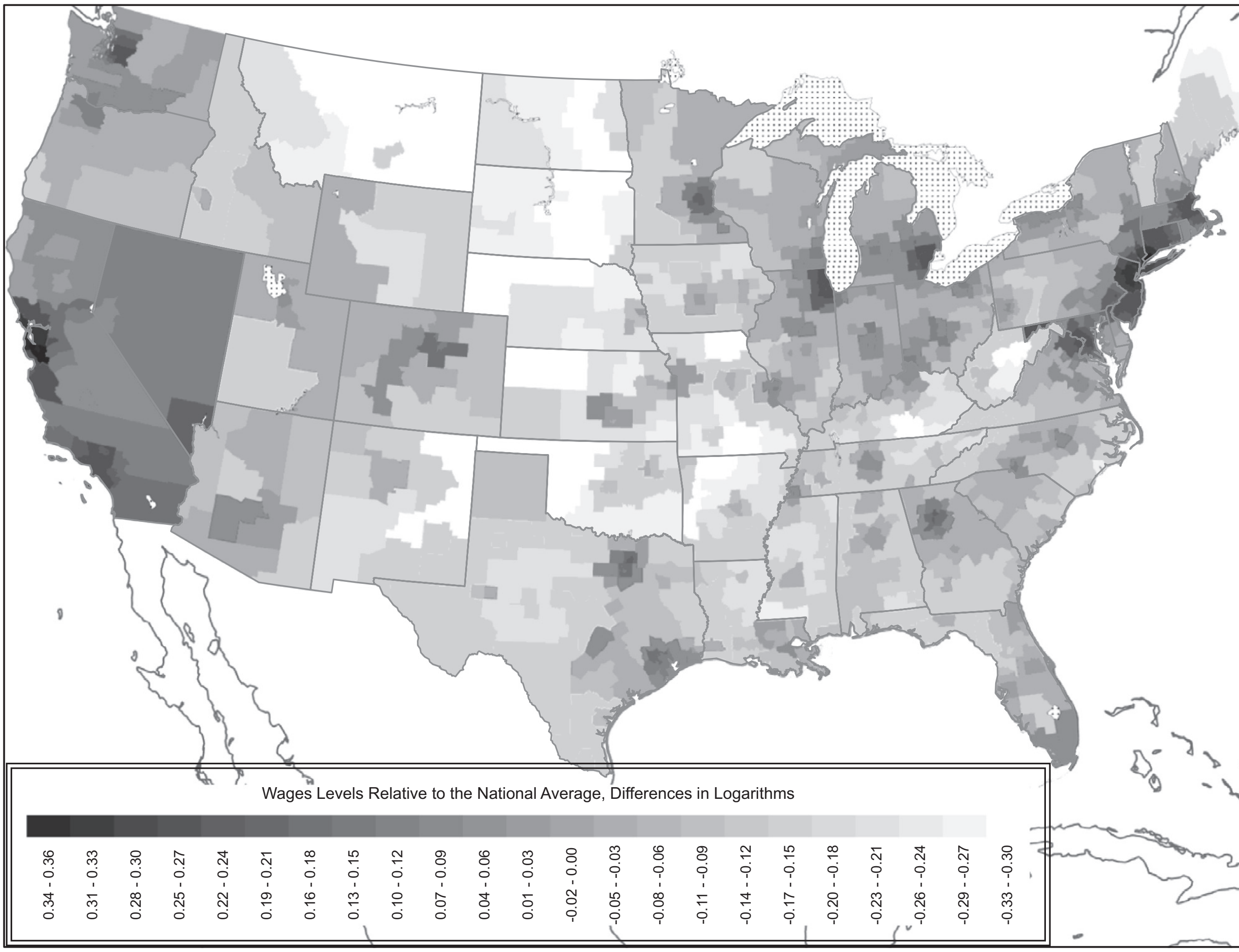
Estimates of wage levels by residence vary much more than commuting costs. The enormous gains workers could make by changing their commuting behavior suggests that residential choices correlated with unobserved skills is influencing those estimates. In Table 2, we see that within Manhattan, the Upper West Side wages by residence are 54% higher than in Washington Heights, even though the two areas are separated only by a 14-min subway ride, costing a $1.50 fare in 2000. Wages by workplace exhibit a much more plausible 5% spread. By residence, wages in the Long Island suburbs are often higher than in Manhattan, but by workplace (the two have different PWPUMAs), wages in Long Island are much lower.[26]

On average, residential wage measures indicate wages are lower in central cities. Place-of-work wage measures are equally high in both; furthermore, they rise with density and eventually fall in the distant suburbs.

Whether we measure wages by residence or workplace, Panel C of Table 1 implies that wages vary far more across metro areas than within them. On the other hand, wages due to observed skills vary much more within metros. This supports the hypotheses that residential sorting is greatest within metro areas, while wage level changes across metros are due largely to local firm productivity.

[25] Note that place of work in the public-use files is only available at the Place of Work Public Use Microdata Area (PWPUMA) level. These number 1240, and are made up of the 2071 standard PUMAs. Selection at this coarser level should be no worse than at the PUMA level (used by Fu and Ross). However, the coarser geography eliminates some wage differences mechanically. Appendix D has more details on PWPUMAs. In Appendix Table A3, we determine that half of the differences between the residential and workplace estimates is due to coarser geography; the remaining half is due to actual commuting. The averaging effect may still reduce potential biases, while introducing new ones if agglomeration effects are highly localized and commutes are short. See Rosenthal and Strange (2001) for more about how agglomeration varies at different levels of geography.

[26] Within San Francisco, wages by residence are 28% higher in the primarily residential Marina-Northeastern area than in the skyscraper-filled Downtown. These areas are adjacent, connected by a walk, short drive, or bus ride. Morning commuters head Downtown, contrary to the residential wage gradient. Again, place-of-work wages are much more plausible, exhibiting a 1% difference.



(B)

Fig. 1 (*continued*)

The differences between residence and workplace wage measures provides an index of unobserved skills. In Fig. 2, this index equals the rightward distance from the diagonal to each PUMA's marker, e.g. unobserved skills are high in Alpharetta and low in East Harlem. Across PUMAs, a one-point increase in observed skills predicts a half-point increase in this unobservable skill measure, and is stronger within MSAs. In column 6 of Table 2 both observed and unobserved skill levels are low in Harlem and Bayview, and high in the Upper East Side and N.E. San Francisco. In conclusion, using wages by residence will likely bias quality-of-life estimates upwards in areas with low-skilled workers, confusing them for areas where jobs offer low wages.

4.4. Commuting costs

We estimate commuting-costs using reported commuting times and modes from the same sample used for wages. We regress the square root of commute time, with place-of-residence indicators, μ_f^j, and controls, X_{fi}^j. The controls are the same as in the wage equation, plus controls for children – each interacted with gender. Thus, the regression equation is

$$\sqrt{f_i^j} = X_{fi}^j \beta_f + \mu_f^j + \varepsilon_{fi}^j. \tag{8}$$

We use the square root as it fits the data well and accommodates reports of zero commuting time. The differential is then constructed using $\hat{f}^j = 2\mu_f^j/\overline{\sqrt{f}}$, where $\overline{\sqrt{f}}$ is the average of square-root commuting time.[27]

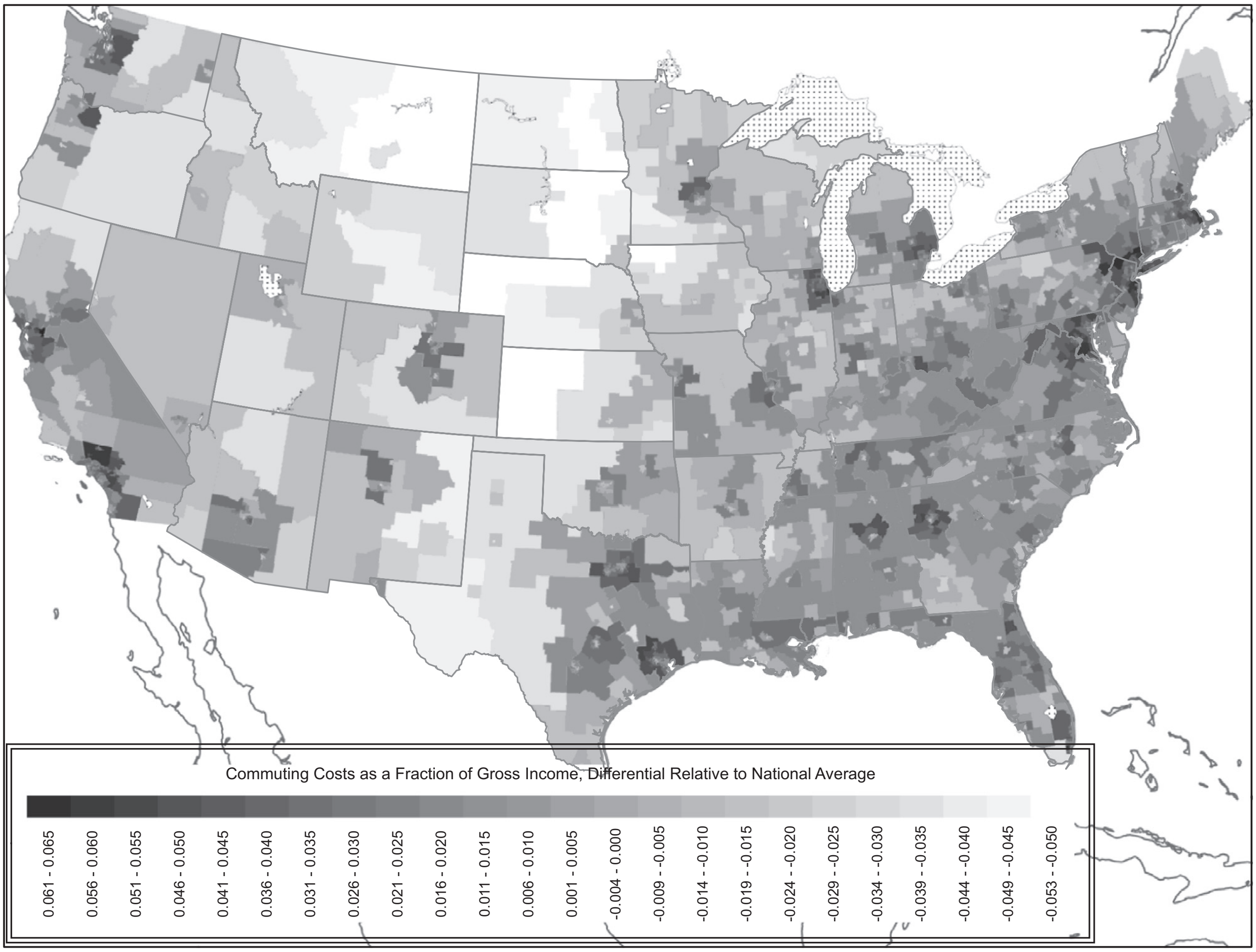
We assume that the time–cost of commuting, α, is independent of transportation mode, and that transportation mode determines monetary costs. Using a linear probability model, we calculate demographically-adjusted probabilities of using each mode of transportation, ρ_l^j, for modes l – own car, carpool, public transportation, and other methods (e.g. walking and biking). The monetary cost of commuting, represented by $s_c\hat{f}^{jk}$, is the weighted average of the mode costs multiplied by the time differential, plus the deviation in average monetary costs:

$$s_c\hat{f}^{jk} = \sum_l \rho_l^j c_l \hat{f}^j + \sum_l \left(\rho_l^j - \bar{\rho}\right) c_l.$$

Outside of New York City, these modal adjustments are minor since most people drive.[28] The appendix details these methods and summarizes the component measures in Table A4.

[27] The R-squared is 0.08 using the square root. Using powers of 0.25 and 1 (linear) caused worse fits. We forgo discussion of time predicted by observable characteristics, which have little predictive power.

[28] Within the city borders of New York, San Francisco, Boston, Philadelphia, and Chicago, the monetary costs of transit riders are independent of travel time, as their transit agencies charge a flat fare.



(C)

Fig. 1 (*continued*)

Column 7 in Tables 1 and 2 report the index of commuting costs, $\hat{c}^{jk}$, the last term of (5). It depends primarily on commuting times, reported in column 8. Consistent with standard urban models, these costs are lower in central cities than in the suburbs. These costs are lowest in non-metro areas where labor markets are more dispersed. They vary slightly less within metropolitan areas than across them. The map in Fig. 1C, illustrates these facts. In large metros like Atlanta, Dallas, and Houston, commuting costs exhibit a remarkable annulus or "donut" pattern around their central cities. In other metros, the patterns are more asymmetric: in Detroit they rise going north; in Boston they rise heading south towards Cape Cod. The highest commuting times nationwide are on the outskirts of New York, Los Angeles, Chicago and Washington D.C. The lowest costs are in remote areas, particularly in the Great Plains.

Fig. 3 plots commuting costs relative to rents within metro areas that contain multiple PUMAs. A one-point increase in commuting costs is associated with a 3.5 point reduction in rents, or a 2.8 point reduction when controlling for wage-levels by place of work. This negative relationship agrees with rent-gradient predictions that the slope should be -3.0 according to our parametrization of Eq. (5), holding quality of life constant. This supports our parametrization and the view that rent gradients are determined by wage opportunities and commuting costs, even if the gradients are not always mono-centric.

4.5. Household characteristics

Table 3 reports how several household characteristics diverge spatially. Some characteristics vary little. The average proportion of children under 18 is 27% across central cities, suburbs, and non-metro areas; it does not change with density either. The standard deviation is 4 percentage points across PUMAs. Those over 65 are located slightly more in non-metropolitan and low-density areas. About 50% of the population is in the labor force; this number is only 1% higher in the suburbs and in medium-density areas. Household size also varies little. Marriage rates among adults are somewhat lower in central cities relative to the suburbs and non-metro areas.

Differences related to education, race, and ethnicity are more substantial. College degrees are relatively rare outside metro areas. Within metros, college attainment varies considerably, although the difference between central cities and suburbs is small. Blacks are more likely to reside in central cities, constituting 20% of the population there. Immigrant status is also concentrated in urban and dense areas, and varies more across metro areas than within.

Table 2
Rent, wage, commuting-cost, and quality-of-life differentials within Manhattan and San Francisco, 2000.

Area name	Population	Rents/hous. cost		Wage			Commuting		Quality of life		
		Location index or "Rent"	Comp. or "Quality"	Index by workplace	Index by residence	Comp. or "Skill"	Index of full cost	Time diff. only	Workpla. adj. index	Simple (not used)	QOL rank from (9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
New York Co., NY	*1,537,195*	*0.762*	*−0.528*	*0.255*	*0.282*	*0.002*	*−0.001*	*0.185*	*0.127*	*0.086*	*23*
Upper East Side	217,063	1.409	−0.499	0.273	0.483	0.224	−0.003	0.159	0.327	0.191	1
Stuy Town/Turtle Bay	143,441	1.315	−0.556	0.270	0.434	0.194	−0.017	−0.014	0.284	0.176	7
Greeewich Vlg./Fin. District	125,567	1.284	−0.535	0.272	0.411	0.185	−0.018	−0.081	0.272	0.182	10
Upper West Side	192,213	1.223	−0.535	0.272	0.463	0.208	−0.002	0.142	0.268	0.139	12
Midtown West/Chelsea	122,241	1.078	−0.549	0.270	0.419	0.125	−0.022	−0.118	0.202	0.105	41
Washington Hts./Inwood	216,234	0.289	−0.564	0.225	0.052	−0.222	0.020	0.499	0.008	0.066	820
Morningside Hts./Hamilton Hts.	129,533	0.291	−0.510	0.235	0.110	−0.088	0.008	0.322	−0.008	0.040	993
Lower E. Side/Chinatown	166,379	0.353	−0.548	0.252	0.075	−0.132	−0.006	0.151	−0.009	0.031	996
Central Harlem	109,091	−0.039	−0.474	0.237	0.199	−0.186	0.011	0.305	−0.113	−0.106	1998
East Harlem	115,433	−0.053	−0.474	0.236	0.133	−0.199	0.01	0.352	−0.117	−0.081	2006
San Francisco City & Co., CA	*776,733*	*1.031*	*−0.264*	*0.262*	*0.250*	*−0.002*	*0.008*	*0.185*	*0.218*	*0.186*	*3*
Marina/North Beach/Nob Hill	107,285	1.225	−0.408	0.266	0.387	0.087	−0.002	0.105	0.267	0.179	13
Ingleside	105,194	1.137	−0.155	0.260	0.258	0.007	0.018	0.265	0.261	0.230	14
Sunset	105,532	1.105	−0.215	0.268	0.229	0.050	0.021	0.350	0.251	0.226	17
Beuna Vista/Central/Bernal Hts.	109,355	1.134	−0.266	0.266	0.255	0.077	0.006	0.165	0.247	0.210	21
Richmond/W. Addition	136,975	1.047	−0.269	0.265	0.266	0.053	0.011	0.217	0.225	0.179	30
Downtown/SOMA/Mission	107,054	0.880	−0.361	0.257	0.183	−0.109	−0.014	−0.037	0.152	0.154	103
S. Bayshore/S. Central	105,338	0.681	−0.166	0.248	0.169	−0.200	0.013	0.223	0.118	0.126	170

Differentials are relative to the national average and are expressed in logarithms or logarithm equivalents. The sub-county measures are for Public-Use Microdata Areas, each containing over 100,000 inhabitants. Area names for the PUMAs here are based on sub-borough and planning area names from the Census. To offset bias due to rent control, the fraction of units that are controlled was multiplied by ln(1.37) in the six lower sub-boroughs of Manhattan and by ln(1.19) in San Francisco. Quality-of-Life Rankings are out of 2071 PUMAs.

Home ownership rates are much higher in suburban and low-density areas, although this is strongly related to the presence of single-family buildings.

5. Quality of life across the United States

We combine the rent, wage, and commuting differentials to estimate average local willingness-to-pay – or, "quality of life" – from Eq. (5).[29] The geographic units provided by the Census allows us to map quality of life with some detail: Fig. 4 covers the continental United States, and Fig. 5A–D cover areas around San Francisco, New York, Detroit, and Atlanta respectively. Quality-of-life differentials for these four MSAs, and for Honolulu, are presented in Table 4.[30] In these locations, we aggregate our quality-of-life estimates according to four levels of geography: MSA-equivalents, PMSA-equivalents, counties, and PUMAs. Each level of geography is given its own ranking by type, so there are separate rankings for each of these four geographic levels.[31] Table A1 ranks and list quality-of-life differentials across all 2071 PUMAs.

The highest quality-of-life PUMA in the United States is the Upper East Side of New York City, famous for its museums and proximity to Central Park. Second is a PUMA that contains the affluent Los Angeles neighborhoods of Brentwood and Bel Air, at the base of the Santa Monica mountains. The third PUMA contains Los Gatos and Cupertino, the home of Apple Inc., in the heart of Silicon Valley. The fourth PUMA contains the communities of East Oahu, including Waialae-Kahala – known for its secluded beaches and accessibility to Honolulu and Diamond Head. Rounding out the top 5 is the PUMA containing the scenic communities of Sausalito, Mill Valley, and San Rafael, just north of San Francisco and the Golden Gate Bridge. To live in these places, households sacrifice the equivalent over 26% (30 log points) of real after-tax income relative to the national average.

The highest ranked county is Marin, CA, whose county seat is San Rafael. The second and third ranked counties are San Mateo and San Francisco (see Fig. 5A). Together, these three counties comprise the San Francisco PMSA, which ranks first among PMSA equivalents. When San Francisco is combined with its nearby PMSAs, including Santa Cruz (#3), San Jose (#4) and Oakland (#8), to form a larger CMSA it ranks second after Honolulu.[32]

New York City is a particularly interesting case. Manhattan, a 34 square-mile island, is split into 10 quite different sub-boroughs (see Fig. 5B). While the labor market on the island appears unified, the rents vary tremendously relative to commuting costs, signaling major differences in quality of life. Five of the sub-boroughs rank in the top 25 PUMAs, while two are in the bottom 100. Most locals are quite aware of these often discontinuous differences in neighborhood desirability, such as between the Upper East Side and East Harlem. As these neighborhoods share the same geography, climate, and municipality, these contrasts raise the issues mentioned earlier regarding heterogeneous populations, endogenous amenities, and sorting. Suburban areas in Long Island and New Jersey show considerable discrepancies in quality of life as well.

The lowest quality of life is found in southwest Detroit, in the area containing the neighborhoods of Chadsey, Condon, and Vernor (see Fig. 5C). Households are compensated with 25% (23 log points) higher real income to live here. The Detroit MSA is relatively

[29] The estimates include adjustments for state taxes and housing deductions. Refer to Appendix C for details.

[30] We also estimated the quality-of-life differentials separately for whites and non-whites. The relationship between the two was nearly one-to-one, with a correlation of over 0.8. This is remarkable given possible noise in the data as well as segregation within PUMAs.

[31] All measures not at the PUMA level are population weighted means of PUMA estimates.

[32] In the SF Bay Area, Blomquist et al. (1988) found Alameda County, which contains the central city of Oakland, to be one of the best counties, and Marin County, one of the worst. Among other things, this is probably due to their use of wage levels based on residence rather than place of work, since unobserved skill levels in Marin are high. As explained in Albouy (2008), the SF Bay Area was assigned a low quality of life in their article as they did not take into account federal taxes and non-housing costs-of-living.

Table 3
Household characteristics, within, across, and outside U.S. Metropolitan Areas, 2000.

	Percent under 18	Percent over 65	Percent of adults married	Household size	In labor force	College Degree over 25	Race:black	Immigrant	Renter status
Panel A: Central city, suburban, or non-metropolitan area									
Central city (in metro)	0.27	0.12	0.50	2.59	0.49	0.31	0.20	0.18	0.44
Suburban (in metro)	0.27	0.12	0.62	2.68	0.51	0.32	0.09	0.12	0.27
Non-metropolitan areas	0.27	0.15	0.63	2.53	0.47	0.20	0.09	0.04	0.23
Panel B: By residential population density									
>5000 per square mile	0.27	0.12	0.50	2.72	0.48	0.32	0.19	0.26	0.46
1000–5000 per square mile	0.27	0.12	0.60	2.60	0.51	0.33	0.11	0.09	0.28
<1000 per square mile	0.27	0.14	0.64	0.257	0.48	0.22	0.09	0.04	0.22
Panel C: Standard deviations									
All PUMAs	0.041	0.042	0.091	0.329	0.055	0.137	0.170	0.126	0.142
Across metropolitan areas	0.022	0.029	0.035	0.200	0.035	0.076	0.095	0.101	0.069
Within metropolitan areas	0.035	0.029	0.060	0.259	0.042	0.156	0.143	0.077	0.129
Fraction of variance within	*0.729*	*0.477*	*0.435*	*0.620*	*0.583*	*1.297*	*0.708*	*0.373*	*0.825*

Data are taken from the U.S. Census 2000 IPUMS for 2071 Public-Use Microdata Areas (PUMAs). See Table 1 and text for greater detail.

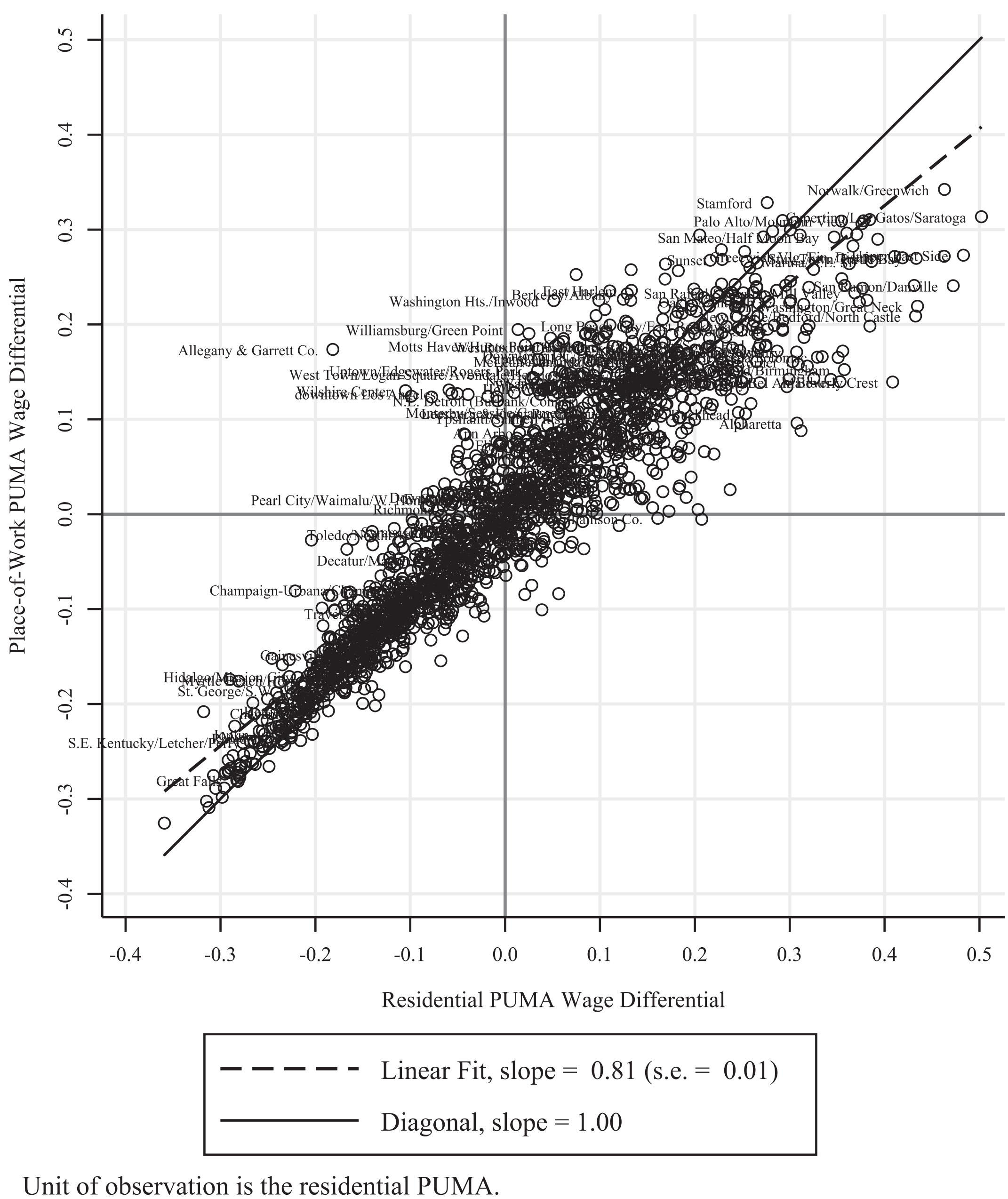
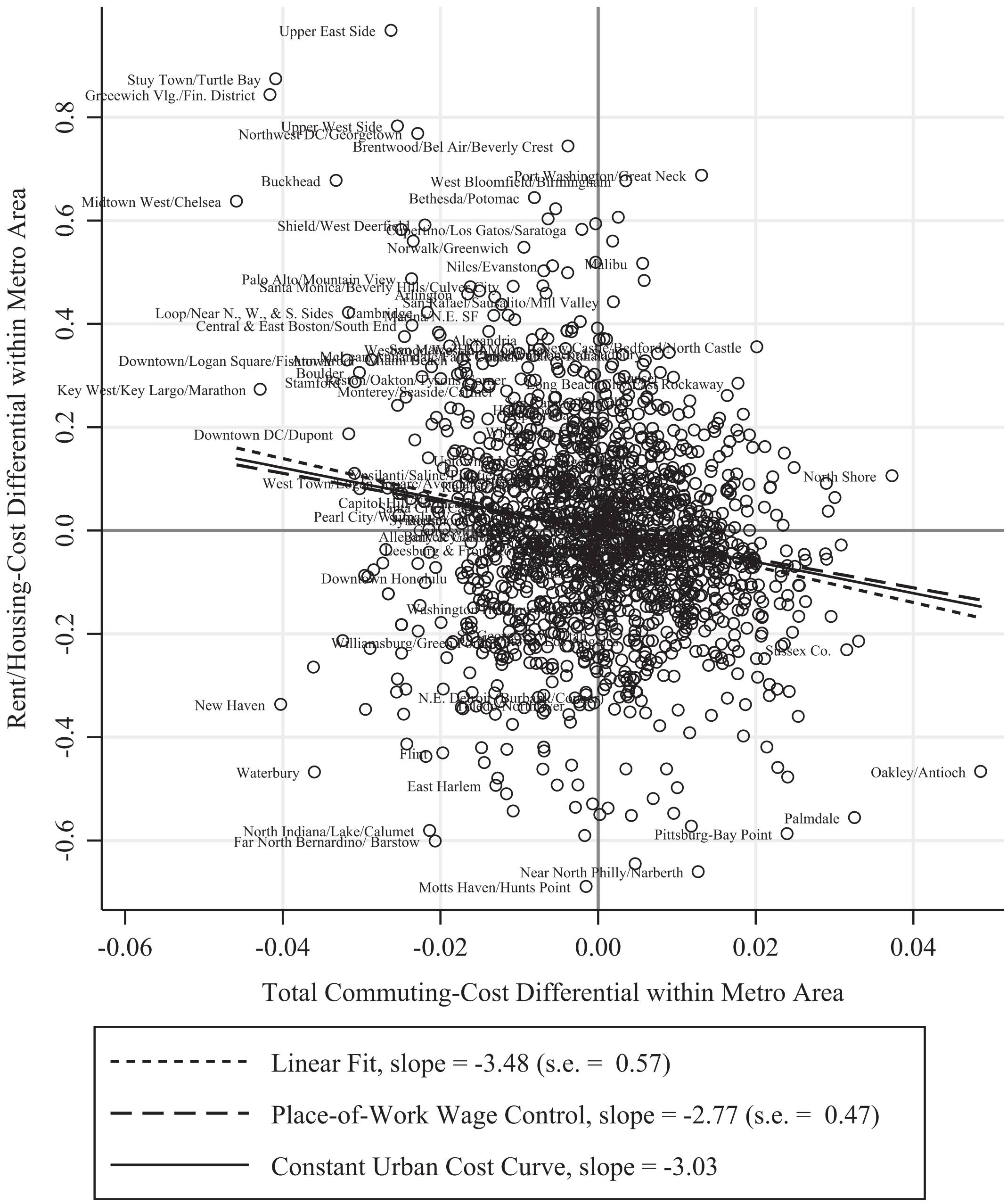


Fig. 2. Wages estimated by workplace or by residence, 2000.



Housing and commuting-cost differentials are residuals from separate regressions on metro-area (MSA/CMSA) indicators (i.e., fixed effects).

Fig. 3. Rents and commuting costs, 2000.

undesirable on average, though the suburbs of West Bloomfield and Birmingham are in a top 100 PUMA. Detroit has two satellite PMSAs, Flint and Ann Arbor, with contrasting central cities. Both have similar wages and commutes, but the higher rents in Ann Arbor signal its more attractive amenities.

Quality of life discrepancies in Atlanta, GA (Fig. 5D) are less stark. The greatest range is within the city limits: Buckhead is the highest and Center Hill/West Lake is the lowest, with Midtown/Downtown in-between.

Each metro area has its idiosyncrasies, although some national patterns emerge in column 9 of Table 1. On average, the typical household prefers suburban areas to central cities, as they pay 2% more in rents, and endure commutes 7% longer to get the same wages. Quality of life in central cities is still 6% of income higher than outside of metro areas altogether.

Quality of life is higher in denser areas. This does not prove that density is itself desirable: more people should want to live in amenable areas, although local housing supply restrictions may impede them. Twenty percent of suburbs have over 5000 residents per square mile, where quality of life is 7% above average. Some central-city areas have densities under 5000, such as downtown Kansas City, MO: these areas offer a quality of life 2% below average.

The results in Panel C reveal almost as much variation in quality of life within metro areas as across them. The standard deviation in values is 5% within metros and 6% across.[33] This

[33] While the variation within metro areas appears slightly lower than the variation across, it is probably understated, since PUMAs obscure variation at lower levels of geography. Thus, there is likely to be even more variation within metros than across metros.

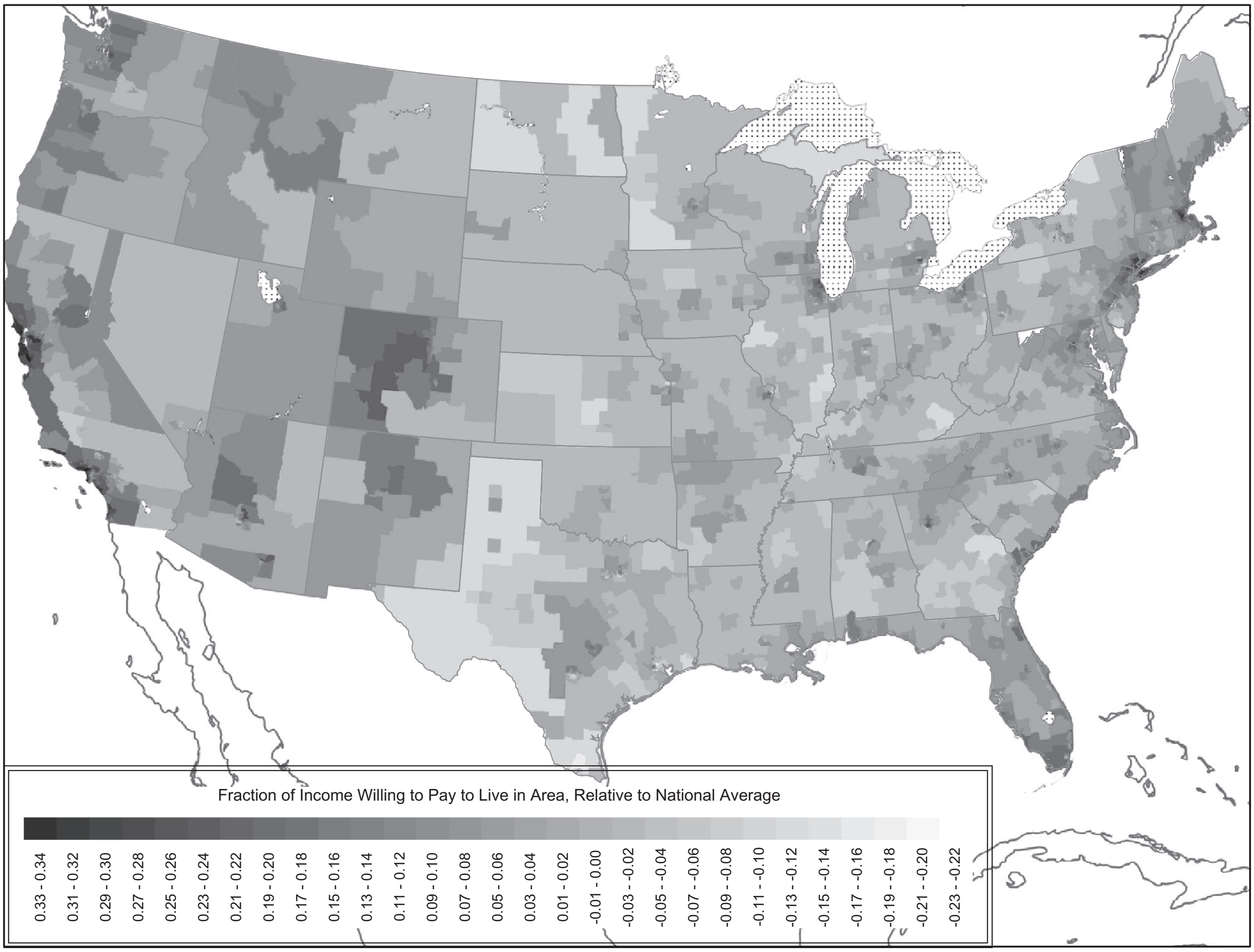


Fig. 4. Quality of life across the United States, 2000.

variation is remarkable given that rents, and especially wages, vary less within MSAs than they do across them. This suggests that, geographically, a metro area's labor market is more homogeneous than its amenities.

To highlight the importance of commuting, column 10 presents quality-of-life estimates that ignore commuting costs and use place-of-residence wages. These estimates make central cities look more desirable to typical households than the suburbs.[34]

6. Predictors of sub-metropolitan quality of life

The quality-of-life index should capture the value of all amenities, many of which may be very difficult to observe, such as smells, beautiful gardens, friendly residents, or charming architecture. Nevertheless, it is reassuring if the quality-of-life index has significant partial correlations of the "correct" sign for ostensibly desirable amenities. We model this relationship using the regression equation

$$\hat{Q}^j = \sum_k \pi_k^Q Z_k^j + \varepsilon^{Qj}. \tag{9}$$

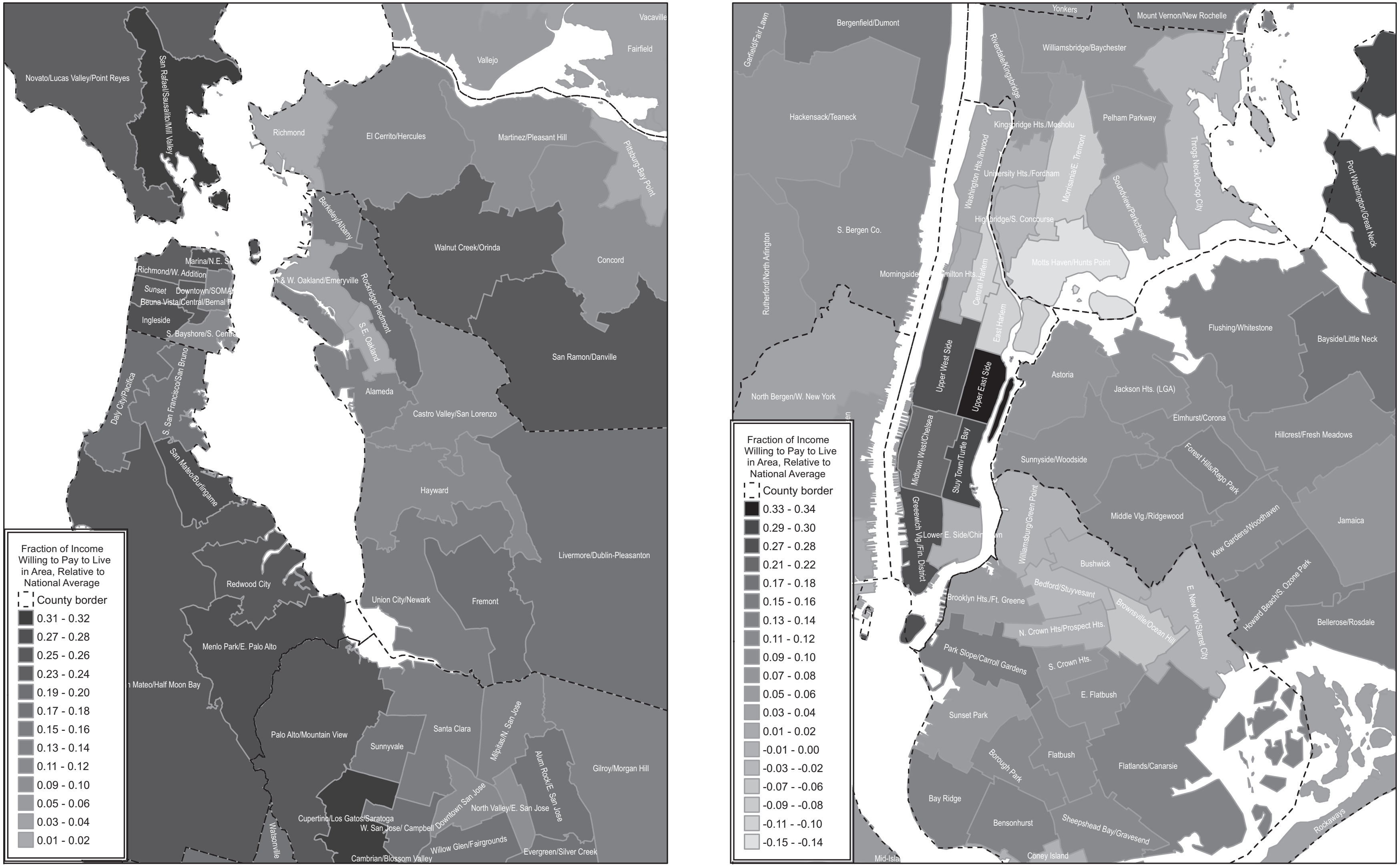
In a hedonic framework, where amenities are exogenous and households have the same preferences, this relationship can be taken as causal. The regression coefficients would then be $\pi_k = -(\partial E/\partial Q)\left(\partial\tilde{Q}/\partial Z_k\right)\Big/\bar{m}$, i.e., the fraction of gross income a household is willing to pay for one more unit of amenity k.[35] The residual ε^{Qj} results from measurement error, unobserved amenities, mis-specification, and unobserved housing quality and worker skills. In practice, the requirements needed for this regression to have an error term orthogonal to the amenity measures are not met.[36] Thus, the dollar values we give are merely illustrative. More uniquely, we examine whether estimates within metro areas are similar to those identified across all areas by adding MSA indicators, or "fixed effects," to the regression. This reduces the identifying variation, but may provide some insights, particularly if confounding effects are different within metro areas relative to across them.

Our amenity variables are described in Appendix B, and summarized in Table 5. The three climate variables – measuring cold, heat, and sunshine – vary little within metros. The geography measures – average slope of land and inverse distance to the coast – vary more within. We also use three amenity variables that are largely endogenous to the local population and available nationwide only at the county level. We proxy for safety using the negative murder rate. It varies more within metros than across;

[34] They also lower rankings of large metro areas relative to smaller ones, and to non-metro areas. Without commuting, the San Francisco CMSA drops from 2 to 3, New York from 12 to 36, Atlanta from 70 to 146, and Detroit from 156 to 225.

[35] Multiplying this coefficient by average gross household income ($68,000 in 2000) produces a dollar value.

[36] Amenities are often collinear, making it hard to get precise estimates for a large set of variables. Unmeasured amenities may contribute to omitted variable biases. Artificial amenities may be endogenous to other determinants of quality of life, including local populations with heterogeneous preferences. There may also be important non-linearities in the hedonic equation.



(A)

(B)

Fig. 5. (A) Quality of life in the San Francisco Bay Area, 2000. (B) Quality of life in and around Manhattan, 2000. (C) Quality of life in Detroit and Southeast Michigan, 2000. (D) Quality of life in and around Atlanta, 2000.

Fig. 5 (*continued*)

Table 4
Rent, wage, commuting-cost, and quality-of-life differentials for four levels of geography within five metropolitan areas, 2000.

Area name	Unit of geography	Population (1)	Housing cost index (2)	Wage by workplace (3)	Full commute cost (4)	QOL adj. (5)	QOL rank in geog. unit (6)
Honolulu, HI	**MSA**	**876,156**	**0.618**	**0.017**	**0.001**	**0.195**	**1**
East Oahu/Waialae-Kahala	PUMA	102,724	0.958	0.017	0.005	0.306	4
Kaneohe/Kailua	PUMA	117,994	0.761	0.016	0.009	0.249	18
Pearl City/Waimalu/W. Honolulu	PUMA	144,481	0.646	0.016	−0.008	0.196	45
Waikiki/Alo Maoni/Kapiolani	PUMA	109,509	0.700	0.018	−0.025	0.194	48
Waipahu/Mililani/Ewa	PUMA	178,534	0.476	0.018	0.024	0.174	69
Downtown Honolulu	PUMA	109354	0.526	0.018	−0.016	0.149	105
West Oahu/Midway Islands	PUMA	113560	0.357	0.019	0.008	0.119	169
San Francisco-Oakland-San Jose, CA	**MSA**	**7,039,362**	**0.809**	**0.243**	**0.012**	**0.159**	**2**
San Francisco, CA	PMSA	1,731,183	1.078	0.266	0.008	0.230	1
Marin Co.	*County*	*247,289*	*1.138*	*0.231*	*0.017*	*0.273*	*1*
San Rafael/Sausalito/Mill Valley	PUMA	146,373	1.251	0.233	0.014	0.304	5
Novato/Lucas Valley/Point Reyes	PUMA	100,916	0.974	0.228	0.022	0.227	29
San Mateo Co.	*County*	*707,161*	*1.109*	*0.283*	*0.006*	*0.230*	*2*
San Francisco Co.	*County*	*776,733*	*1.031*	*0.262*	*0.008*	*0.218*	*3*
Santa Cruz-Watsonville, CA	PMSA	255,602	0.799	0.164	0.006	0.185	3
San Jose, CA	PMSA	1,682,585	0.977	0.302	0.006	0.180	4
Santa Rosa, CA	PMSA	458,614	0.577	0.134	0.004	0.125	7
Oakland, CA	PMSA	2,392,557	0.638	0.233	0.020	0.118	8
Vallejo-Fairfield-Napa, CA	PMSA	518,821	0.359	0.154	0.010	0.054	36
NYC, N. NJ, Long Is., NY-NJ-CT-PA	**MSA**	**22,767,645**	**0.430**	**0.198**	**0.023**	**0.067**	**12**
Nassau-Suffolk, NY	PMSA	2,753,913	0.541	0.185	0.030	0.117	9
New York, NY	PMSA	9,314,235	0.473	0.202	0.027	0.086	20
Westchester Co.	*County*	*923,459*	*0.678*	*0.212*	*0.025*	*0.145*	*17*
New York Co. (Manhattan)	*County*	*1,537,195*	*0.762*	*0.255*	*−0.001*	*0.127*	*23*
Putnam Co.	*County*	*95,745*	*0.478*	*0.191*	*0.053*	*0.117*	*31*
Queens Co.	*County*	*2,229,379*	*0.500*	*0.192*	*0.037*	*0.108*	*43*
Richmond Co. (Staten Island)	*County*	*443,728*	*0.449*	*0.191*	*0.049*	*0.104*	*47*
Rockland Co.	*County*	*286,753*	*0.491*	*0.182*	*0.024*	*0.097*	*54*
Kings Co. (Brooklyn)	*County*	*2,465,326*	*0.361*	*0.184*	*0.031*	*0.061*	*117*
Bronx Co.	*County*	*1,332,650*	*0.168*	*0.192*	*0.030*	*−0.006*	*525*
Bergen-Passaic, NJ	PMSA	1,373,167	0.551	0.220	0.012	0.083	22
Stamford-Norwalk, CT	PMSA	882,567	0.603	0.270	0.010	0.075	24
Danbury, CT	PMSA	1,064,760	0.535	0.245	0.009	0.064	29
Middlesex-Somerset-Hunterdon, NJ	PMSA	1,549,507	0.400	0.223	0.025	0.046	43
Newark, NJ	PMSA	2,030,197	0.393	0.216	0.020	0.041	47
Monmouth-Ocean, NJ	PMSA	1,330,939	0.279	0.171	0.034	0.039	52
Bridgeport, CT	PMSA	701,891	0.411	0.209	0.003	0.034	56
Dutchess County, NY	PMSA	277,140	0.163	0.105	0.021	0.022	73
Newburgh, NY-PA	PMSA	477,918	0.095	0.079	0.030	0.021	76
Jersey City, NJ	PMSA	612,562	0.345	0.235	0.019	0.017	79
Waterbury, CT	PMSA	413,598	0.204	0.141	−0.001	−0.005	117
New Haven-Meriden, CT	PMSA	870,785	0.208	0.143	−0.002	−0.006	118
Trenton, NJ	PMSA	350,093	0.249	0.197	0.005	−0.011	128
Atlanta, GA	**MSA**	**4,112,198**	**0.025**	**0.062**	**0.018**	**−0.002**	**70**
DeKalb Co.	*County*	*665,865*	*0.133*	*0.076*	*0.018*	*0.026*	*267*
Fulton Co.	*County*	*816,006*	*0.171*	*0.093*	*0.006*	*0.019*	*299*
Cobb Co.	*County*	*607,751*	*0.092*	*0.079*	*0.022*	*0.016*	*313*
Forsyth & Pickens Cos.	*County*	*121,390*	*0.015*	*0.042*	*0.023*	*0.006*	*440*
Cherokee Co.	*County*	*141,903*	*−0.015*	*0.046*	*0.029*	*0.004*	*406*
Gwinnett Co.	*County*	*588,448*	*0.023*	*0.067*	*0.023*	*−0.004*	*579*
Coweta, Fayette, & Spalding Cos.	*County*	*238,895*	*−0.119*	*0.017*	*0.015*	*−0.030*	*905*
Henry Co.	*County*	*119,341*	*−0.193*	*−0.004*	*0.021*	*−0.036*	*1185*
Carroll & Douglas Cos.	*County*	*179,442*	*−0.201*	*−0.002*	*0.020*	*−0.044*	*1128*
Bartow & Paulding Cos.	*County*	*157,697*	*−0.226*	*0.017*	*0.035*	*−0.046*	*1183*
Newton & Rockdale Cos.	*County*	*132,112*	*−0.167*	*0.021*	*0.017*	*−0.047*	*1189*
Barrow & Walton Cos.	*County*	*106,831*	*−0.221*	*0.009*	*0.026*	*−0.049*	*1260*
Clayton Co.	*County*	*236,517*	*−0.119*	*0.056*	*0.012*	*−0.051*	*1304*
Detroit-Ann Arbor-Flint, MI	**MSA**	**5,456,428**	**0.031**	**0.117**	**0.008**	**−0.039**	**156**
Ann Arbor, MI	PMSA	578,736	0.141	0.079	0.003	0.009	93
Livingston Co.	*County*	*156,951*	*0.187*	*0.101*	*0.024*	*0.035*	*219*
Washtenaw Co.	*County*	*322,895*	*0.220*	*0.096*	*−0.006*	*0.018*	*304*
Ann Arbor	PUMA	114,024	0.364	0.086	−0.021	0.054	453
Ypsilanti/Saline/Pittsfield Twp.	PUMA	208,871	0.142	0.101	0.002	−0.002	915
Lenawee Co.	*County*	*98,890*	*−0.192*	*−0.009*	*0.001*	*−0.059*	*1467*

(continued on next page)

Table 4 (*continued*)

Area name	Unit of geography	Population (1)	Housing cost index (2)	Wage by workplace (3)	Full commute cost (4)	QOL adj. (5)	QOL rank in geog. unit (6)
Detroit, MI	PMSA	4,441,551	0.045	0.129	0.009	−0.038	204
Oakland Co.	*County*	*1,194,156*	*0.277*	*0.146*	*0.012*	*0.032*	*242*
Macomb Co.	*County*	*788,149*	*0.106*	*0.131*	*0.014*	*−0.015*	*652*
St. Clair & Lapeer Co.	*County*	*252,139*	*−0.045*	*0.046*	*0.021*	*−0.018*	*690*
Monroe Co.	*County*	*145,945*	*−0.025*	*0.072*	*0.008*	*−0.036*	*995*
Wayne Co.	*County*	*2,061,162*	*−0.098*	*0.131*	*0.004*	*−0.091*	*2521*
Flint, MI	PMSA	436,141	−0.226	0.060	0.003	−0.099	322

Units of geography are MSA, PMSA, County, and PUMA. MSAs that contain several PMSAs, are also called "CMSAs". The PMSA ranking also includes MSAs that do not contain PMSAs. Counties may be larger, equal to, or smaller than PUMAs. For example, one PUMA contains St. Clair & Lapeer counties, and so they are listed together. Only some sub-geographies are shown. All of the PUMAs are contained in Appendix Table A1. The rankings in column 6 are different for each type of geography, and are indented at the same levels as the names. Our rankings are out of 3202 counties or equivalents (parishes, boroughs, independent cities, census areas), 2071 PUMAs, 332 PMSAs, and 276 MSAs.

Table 5
Selected amenities within, across, and outside U.S. Metropolitan Areas, 2000.

	Annual heating degree days (1)	Annual cooling degree days (2)	Annual sunshine percent possible (3)	Inverse distance to coast (4)	Average slope of land (4)	Murder rate per 1000 (5)	Restaurants and bars per 1000 (6)	Public school revenues per student (7)
Panel A: Central city, suburban, or non-metropolitan area								
Central city (in metro)	3.98	1.40	0.62	0.13	0.01	0.09	1.80	0.81
Suburban (in metro)	4.31	1.28	0.60	0.07	0.02	0.05	1.68	0.85
Non-metropolitan areas	5.15	1.13	0.59	0.02	0.02	0.04	1.68	0.75
Panel B: By residential population density								
>5000 per square mile	3.71	1.28	0.63	0.19	0.01	0.09	1.80	0.88
1000–5000 per square mile	4.49	1.33	0.60	0.05	0.02	0.05	1.73	0.82
<1000 per square mile	4.79	1.22	0.59	0.02	0.02	0.04	1.61	0.75
Panel C: Standard deviations								
All PUMAs	2.199	0.912	0.079	0.158	0.022	0.057	0.477	0.168
Across metropolitan areas	2.155	0.888	0.078	0.094	0.016	0.035	0.279	0.153
Within metropolitan areas	0.438	0.208	0.012	0.127	0.014	0.046	0.387	0.070
Fraction of variance within	*0.040*	*0.052*	*0.023*	*0.646*	*0.405*	*0.651*	*0.658*	*0.174*

Data are taken from sources described in the appendix. Murder rate, restaurants and bars and public school revenues are at the county level. Cooling and heating degree days are from a 65 F base. Revenues per student are measured in $10,000 units. See text for greater detail.

murders are more common in central and dense areas. The same is true of the number of bars and restaurants per capita, which is our proxy of local entertainment. Public school revenues exhibit less variation within metros. This mirrors local wage levels, which are likely the main source of cost differences through salaries. School revenues are higher in the suburbs. In general, because artificial amenities are largely produced by local residents, our estimates may reflect the desirability of the populations that produce them.

Table 6 reports the estimates from the amenity regressions. The eight variables explain 40% of the variation in quality of life over all 2071 PUMAs. The finding that households value areas with mild winters, mild summers, sloped land, sunshine, and coastal proximity echoes those of Albouy (2008) for metro areas; Albouy et al. (2013) explore the influence of climate in greater depth. The main observation here is that the coefficients for temperature and slope are still relatively precise and larger within metros. The sunshine estimate becomes imprecise, as there are fewer weather stations measuring sunshine than there are metro areas. Fixed effects cause the estimate for coastal proximity to become small and insignificant. This may be the result of how coastal proximity is measured, or because residents in communities near the coasts find that "close is good enough," in the words of Schmidt and Courant (2006).

The estimates for artificial amenities do not change substantially when metro fixed effects are included, with the exception of crime. Whether this is due to particular household sorting within metro areas deserves further investigation.

Crime rates are available nationally only at the county level. Nevertheless, the regressions here associate an increase in the murder rate from 10 to 20 per 100,000 residents – the difference between Los Angeles and Philadelphia – with a reduction in willingness-to-pay of $900 per household, or $1800 with fixed effects.[37] The geographic coarseness of the crime measure suggests this measure suffers from a downward bias, while murder's correlation with other crimes and disamenities suggests an upward bias. The estimate is smaller than crime valuations in Bishop and Murphy (2011), based on geographically finer data for the SF Bay Area.

The number of local bars and restaurants is strongly associated with willingness-to-pay. Per 1000, each establishment is associated with $190 rise in willingness-to-pay, or $190,000 total. This is just over a third of the average revenue of a restaurant. This large number likely overstates the value of these establishments, as they are located near other retail and entertainment establishments. They are also in highly visited areas, where residents can afford to eat out. The estimate do not reflect the value of establishments to residents outside the neighborhood.

The estimates reveal a strong positive association with school funding, despite the fact that local taxes are not controlled for. An increase in funding of $1000 per student (or, since there are 0.9 students per household, $900 per household) is associated with

[37] It is worth noting that crime victims may not be residents of the neighborhood where the crime occurred, although our measure is at a fairly broad county level.

Table 6
Amenity predictors of local quality of life.

Dependent variables	All QOL by PUMA (1)	Within MSA Adj QOL (2)
Minus 1000 s of heating degree days, 65 F base	0.022***	0.035***
(mean = 4.50, sd = 2.25)	(0.001)	(0.004)
Minus 1000 s of cooling degree days, 65 F base	0.043***	0.059***
(mean = 1.25, sd = 0.91)	(0.003)	(0.008)
Sunshine, percent possible	0.157***	−0.101
(mean = 0.060, sd = 0.078)	(0.021)	(0.098)
Inverse distance to coast	0.115***	0.021
(mean = 0.71, sd = 0.14)	(0.017)	(0.018)
Average slope of land, in percent	0.608***	0.909***
(mean = 1.80, sd = 2.22)	(0.068)	(0.101)
Minus murder rate per 1000	0.133***	0.263***
(mean = 0.05, sd = 0.053)	(0.033)	(0.030)
Restaurants and bars per thousand	0.029***	0.028***
(mean = 1.71, sd = 0.28)	(0.004)	(0.004)
Public school revenues per student, $10,000 s	0.117***	0.093**
(mean = 0.50, sd = 0.13)	(0.010)	(0.021)
R-squared	0.41	0.64
Number of observations	1948	1948

Robust standard errors shown in parentheses. Regressions weighted by population. Variables are described in the appendix, including Appendix Table 6.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

a quality-of-life increase of about $700. This number is likely biased from well-funded areas being nicer or having more desirable residents. Interpreting this number causally would indicate that schools are underfunded, especially if, on the margin, schools are funded out of local taxes (see Brueckner, 1982). Yet, these estimates have the same order of magnitude as the Cellini et al. (2010) estimates for the value of school facilities and the Black (1999), Bayer et al. (2007), and Caetano (2010) estimates for the value schools with higher test scores.

7. Conclusion

While ranking of neighborhood quality is common in the popular literature, using a single index does involve many simplifications. Nevertheless, our index, based on the consumption "sacrifice" a typical household makes to live somewhere does produce plausible results that should be correlated to many households' tastes. While people may differ on what makes a good neighborhood, it is convenient to have a standardized quality of life measure that reflects "typical" tastes to compare neighborhoods in separate metro areas. Analogously, it can be useful to characterize political views along a single dimension from "liberal" to "conservative," even though political views are multidimensional.

By incorporating commuting and place-of-work wages, our simple quality-of-life model fits in well with the standard model on local rent and wage gradients. The commuting adjustment reveals that willingness-to-pay to live in the suburbs or in dense areas is higher than simpler measures imply. The place-of-work wage adjustment reveals that wages offered in central cities are on average as high as in the suburbs, even though skill levels are not. Overall, neighborhood quality within metro areas appears to vary substantially. Such nearby differences seem to have less to do with natural amenities, and more to do with local residents and the artificial amenities they produce.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jue.2015.03.003.

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