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DRIVING TO OPPORTUNITY:
LOCAL RENTS, WAGES, COMMUTING COSTS AND SUB-METROPOLITAN QUALITY OF LIFE

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ABSTRACT

We examine variation in local wage levels, housing costs, and commuting costs for 2071 areas covering the United States within and across metropolitan areas. In an equilibrium model of residential and workplace choice, we use these measures to construct a willingness-to-pay index for a typical household. When households are sufficiently homogeneous and mobile, this index indicates the perceived value of local household amenities, or "quality of life." Wage levels vary little within metropolitan areas relative to across them, while individual characteristics that predict wages vary more within, suggesting patterns about sorting. Quality of life varies as much within metros as across them, and is typically high in areas that are dense, suburban, mild, safe, entertaining, and have higher school-funding.

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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 it some 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.

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,

[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.

Berger, and Hoehn (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 differences in 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 where 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 weakly with commutes, suggesting that workers travel longer in the pursuit of amenities.

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 for the continental United States, as well as New York, San Francisco, Detroit, and Atlanta. These maps show as much difference 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 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, Mattey, and Wascher (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 larger than previously thought. 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 follow a similar method,

[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 crowdsourced 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, Liu and Yezer (2009) to explain intra-city wage differentials.

[4]A recent unpublished working paper by Bieri, Kuminoff, and Pope (2013) performs an analysis similar to Blomquist, Berger, and Hoehn (1988) at the county-level. They incorporate many of the features new in Albouy

but add refinements helpful for a 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, Berger, and Blomquist (1987) consider how a *city-wide* 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]

(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, Ferreira and Rothstein (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 (2009). 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, Ferreira, and McMillen 2007). Many amenities, like climate or geography, change over long time frames, and so it is sensible to model sorting explicitly. Albouy et al. (2013) do just that using the QOL measures here with the method of Bajari and Benkard (2006) to examine the problem of climate change.

[6]See Kuminoff, Smith, and Timmins (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 Winston (2010) provide an interesting debate on the pros and cons of structural modeling and credible inference.

[7]Turnbull (1992) examines the role of leisure in a related model and concludes that it makes little difference for

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. Gabriel and Rosenthal (1996) provide a useful theory for such an application, but use it to address the spatial mismatch of employment for minorities.[8]

Estimates of local wage and rent levels may be biased by unobserved differences in 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.[9]

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.[10]

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]Work on racial segregation is extremely interesting and important for many areas, including that related to the spatial-mismatch hypothesis. For now, we defer 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]No such method exists to control for unobserved housing quality, although our fears are partly allayed by the lack of correlation between quality and location measures discussed below.

[10]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

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 $c \geq 0$ 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.[11] The resulting household budget constraint is then $x + p^j y + cf^{jk} \leq w^j h + I - \tau(w^j h + I)$. 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:

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

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 $\partial e/\partial p,\ \partial e/\partial f \geq 0$ and $\partial e/\partial w,\ \partial e/\partial Q \leq 0$.

separable, which is unlikely to hold. Some amenities, such as beaches, may be closer substitutes to leisure than others. Colwell, Duhring, and Turnbull (2012) 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.

[11] 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.

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 $df^{jk} \equiv df^j + df^k$ 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.[12] 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, $(1-\tau')\bar{h} \cdot dw^k$.[13] In other words, high wages compensate workers for high urban costs or low amenities.

3.3 Applying and Parameterizing 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

[12] 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.

[13] 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).

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 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) by assigning $s_w = 0.75$, $s_y = 0.33$, and $\tau' = 0.35$. We allow for 25 percent of income to come from non-labor sources, such as transfers and savings. We account for differences in the prices of non-housing goods, which are strongly related to the costs of local housing, by putting a higher weight on rents than the literal expenditure share on housing, which is closer to 0.22. Marginal tax rates are based on average income tax rates, as well as a portion of payroll tax rates and some amount for state taxes, insofar as wages vary within states.[14]

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 percent of the working day, and thus $\bar{f}/\bar{h} = 0.10$.[15]

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

[14]In Appendix C.2 we explain how we adjust marginal rates by state. 35% is merely an average.

[15]Annual commuting time is the product of 418 commuting trips, averaging 26.4 minutes each way. Commute time is assumed to be equal by mode.

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 weigh wages relative to housing and commuting costs. Households with fewer earners, such as retirees, put less importance on wages; households with children may put more importance on housing and commuting costs. Implicit marginal tax rates in taxes and transfers may also differ across households. How the index would change under alternate parameterizations or estimates is uncomplicated. The 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. 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, especially features like schools. In a survey, 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 revealed preferences generally assumes that different groups pay the same rent and relies on differences in relative population frequencies to infer different tastes. While there is much evidence of sorting by race and income across neighborhoods (e.g. Cutler and Glaeser

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

1997 and Ioannides 2004), converting relative frequencies into willingness-to-pay differences has generally relied 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 suburbs developments, if they 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 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 new residents prefer Decatur to their old location, say Chicago, they should still have a lower willingness-to-pay than existing 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, although this remains an empirical question.

As another example, consider the impact of exclusionary zoning meant to keep out 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, 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, increasing differences in actual neighborhood quality.

4 Wage, Rent, and Commuting-Cost Estimates

4.1 Units of Geography

We estimate wage, rent, and commuting-cost differentials from the 5 percent sample of the U.S. Census in the Integrated Public Use Microdata Series (IPUMS) for 2000 (Ruggles et al. 2004).[17] 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. 1,266 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. 2,654 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 (1999). 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, 331 PMSAs, and 276 MSAs (putting the 55 PMSAs into 19 CMSAs).[18]

[17]We acknowledge that the quality-of-life estimates are slightly dated. Nevertheless, the 2000 Census offers the last 5 percent 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.

[18]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. We only truly estimate quality-of-life at the PUMA level; all of our aggregations use

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*.[19] We also classify areas according to residential population density – calculated at the census-tract level and averaged by population – using cut-offs of 1,000 and 5,000 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. 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 of geography in 5 MSAs; Table A1 in the Appendix contains them of 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, interpreted as the flow-cost of housing faced by households. 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 percent (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.[20] The resulting regression equation is

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

population-weighted averages of these PUMA level values.

[19] 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.

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

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.[21]

Identifying the rent differentials requires that mean differences in unobserved housing quality across areas are orthogonal to the location index. This requirement may not hold. 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, "quality of life" may also reflect unobserved housing quality. If these biases are important, it seems likely that the quality-of-life measures would be correlated with measures of observed housing quality. As shown in Appendix Figure A1, the correlation is almost zero, suggesting that unobserved housing quality differences are not systematically correlated with underlying willingness-to-pay for local amenities.[22]

Figure 2A 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 percent higher, on average, in the suburbs than in central cities, despite longer commutes. This fact runs contrary to standard rent-gradient predictions, although from the maps we see that rents do eventually fall away from city centers. Outside of metro areas, rents are 34 percent (41 log points) lower than in suburbs. In Panel B, we see dense areas have the highest rents, as predicted by standard urban models.

[21] Pollakowski (2003) estimates that in core Manhattan areas, the lower 6 neighborhoods, prices for rent-controlled units would be 37 percent 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 percent 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.

[22] For instance, the compositional component of housing cost is very high in parts of suburban Atlanta (e.g. Alpharetta and Snellville), although the location is quite average. Meanwhile, the compositional component 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 value 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.

In column 3, we see that housing quality in central cities is 15 percent lower than in suburbs. Quality also falls by about 10 percent 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 differences in housing quality are considerable, but smaller than differences due to location. In addition, rent levels vary more across metro areas than within them, while the opposite is true of housing quality.

4.3 Wage Levels by Workplace and Residence

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 Figure 2B. 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 differences in observed skills: workers' predicted wages are 4 percent below average in central cities, 3 percent above average in suburbs. This fact is consistent with sorting models when the income elasticity for housing is higher than that for the costs of commuting. Observed skills are also 6 percent lower in high-density areas, and 4 percent higher in medium-density areas. The typical standard deviation is 10 log points, with much of the variation within metro areas, highlighting the importance of income-sorting at the sub-metropolitan level.

The evidence of sorting on observed wage determinants raises concerns about unobserved determinants of wages. To mitigate this problem within metros, we use measures of wage opportunities by place of work, following evidence in Fu and Ross (2013) that workers do not sort across workplaces according to their unobserved skills.[23] Figure 1 graphs wage estimates by place of work against those by residence. We see that the the former vary less than the latter.

Our estimates of wage levels by place of residence vary by amounts too large than would be predicted by commuting costs, suggesting that residential selection based on unobserved skills leads to biases. In Table 2, we see wages by residence vary remarkably in Manhattan. In the Upper West Side they are 53 percent higher than in Washington Heights, even though the two areas are separated only by a 14-minute subway ride, costing a $1.50 fare in 2000. Wages by place of work exhibit a much more plausible difference, with wages only 6 percent higher in the Upper West Side. By place of residence, wages in the Long Island suburbs are often higher than in Manhattan, but by place of work (the two have different PWPUMAs), wages in Long Island are much lower.[24]

On average, residential wage measures indicate wages are lower in central cities, contradicting standard wage-gradient predictions. Place-of-work wages are as high in central cities as in suburbs. Furthermore, they rise with density, as seen in Figure 2B, and eventually fall in the distant suburbs.

Whether we measure wages by place of work or residence, the evidence in Panel C of Table 1 implies that wages vary much more across metro areas than within them. This supports the view that metro areas are sensible labor-market areas. On the other hand, wages due to observed skills vary much more within metro areas than across them. This fact supports the hypotheses that

[23]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, although it may introduce 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.

[24]Within San Francisco, wages by place of residence are 28 percent 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, which would be the wrong direction if the place-of-residence estimates were accurate. Again, place-of-work wages are much more plausible, exhibiting a 1-percent difference.

residential sorting is more important within metro areas than across them, while wage differences across metros are due largely to real differences in local productivity.

The differences between residence and workplace wage measures may be used as an index of unobserved skills. In Figure 1, such differences are illustrated by the rightward distance from the diagonal to each PUMA's marker. Across PUMAs, a one-point increase in observed skills predicts a half-point increase in this unobservable skill measure. This relationship is 20 percent stronger within MSAs, reinforcing the hypothesis that within-metro sorting is strong. In column 6 of Table 2 we see evidence that both observed and unobserved skill levels are low in neighborhoods like Harlem and Bayview, and high in the Upper East Side and N.E. San Francisco. Overall, the evidence suggests that using wages by residence biases quality-of-life estimates upwards in areas with low-skilled workers, which are confused with areas where wage opportunities are poor.

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 better than most power transformations, and as it 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.[25]

We assume that the time costs of commuting, $\left[(1-\tau')s_w \bar{f}/\bar{h} - \alpha \bar{f}/\bar{m}\right] \hat{f}^{jk}$, are independent of transportation mode, and that transportation mode only determines monetary costs. Using a linear probability model, we calculate demographically-adjusted probabilities of using each mode

[25]The R-squared is 0.08 using the square root. Using powers of 0.25 and 1 (linear) caused even worse fits. As the predictive power of the regression is rather low, we forgo discussion of time predicted by observable characteristics.

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.[26] The Appendix details these methods and summarizes the component measures in Table A4.

Column 7 in Tables 1 and 2 report the index of commuting costs, $\hat{c}^{jk}$, the last term of (5), which 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 Figure 2C, 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 Los Angeles, New York, and San Francisco. The lowest costs are typically in more remote areas, particularly in the Great Plains.

Within metro areas, commuting costs obey the predictions of monocentric urban models better than rents and wages. Figure 3 plots commuting costs relative to housing costs, controlling for local wage levels.[27] A one-point increase in commuting costs is associated with a 2.3 point reduction in housing costs. This negative relationship agrees with rent-gradient predictions. When interpreted strictly through equation (5) the calibration predicts the slope should be -3.0, when quality of life is constant. This suggests that residents are commuting longer for better amenities, although measurement error or commuting being more desirable than work are also possible explanations.

[26]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.

[27]Each cost measure is the residual from a simple regression on the local wage level.

4.5 Household characteristics

Table 3 reports how several household characteristics vary spatially. Some of these characteristics vary rather little. The proportion of children under 18 is about 28 percent in central cities, suburbs, and non-metro areas; these means do not change much by density either. The standard deviation is 4 percentage points across PUMAs. 12 percent of those in medium density areas are over 65, and this deviates by only 1 percentage point in high and low density areas. About 50 percent of the population is in the labor force; this number is only 1 percent higher in the suburbs and medium-density areas. Household size also varies little. Marriage rates are 37 percent in the central city versus 45 percent in the suburbs.

Differences related to education, race, and ethnicity are more substantial. College degrees are relatively rare outside metro areas. Within metros, college-degree frequency varies considerably, although the average difference between central cities and suburbs is small. Blacks are much more likely to reside in central cities, constituting 20 percent of the population there. Immigrant status is also concentrated in urban and dense areas, and varies more across metropolitan areas than within. 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 equation (5).[28] The comprehensive geographic information provided by the Census Bureau allows us to map the differentials with some detail: Figure 4 covers the continental United States, and Figures 5A, 5B, 5C, and 5D 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.[29] In these locations, we aggregate our quality-of-life

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

[29]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 0.83. This is remarkable given possible noise in the data as well as segregation within PUMAs.

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.[30] Table A1 ranks and list quality-of-life differentials across all 2071 PUMAs.

The highest quality-of-life PUMA in the United States contains the communities of East Oahu, including Waialae-Kahala – known for its secluded beaches and accessibility to Honolulu, HI and Diamond Head. To live here, households sacrifice the equivalent of 29 log points (25 percent) of real after-tax income relative to the national average. This PUMA is inside the Honolulu MSA, which was already found to be the highest quality-of-life MSA in Albouy (2008).

The highest ranked county is Marin, CA just north of the Golden Gate Bridge. It contains two PUMAs. One, with the communities of San Rafael, Sausalito, and Mill Valley (see figure 5A), is ranked fourth among PUMAs. The second and fourth ranked counties are San Mateo and San Francisco, both in California. Together, these three counties comprise the San Francisco PMSA, which ranks first among PMSA equivalents (as a PMSA-equivalent, Honolulu is second). When San Francisco is combined with other nearby California PMSAs, including Santa Cruz (#3), San Jose (#4) and Oakland (#11), the Combined MSA is ranked second, just behind Honolulu.[31]

New York City's dense and renowned areas are interesting to examine. Manhattan, 2 miles wide and 13 miles long, is split into 10 quite different sub-boroughs (see Figure 5B). While the island appears to be a unified labor market, the rents vary tremendously relative to manageable differences in commuting costs, signalling major differences in quality of life. Four of the sub-boroughs rank in the top 25 PUMAs, while two are in the bottom 50. Most locals are quite aware of these differences in neighborhood desirability, some rather discontinuous, such as between the Upper East Side and East Harlem. As these areas share the same geography, climate, and municipality, these differences raise the issues mentioned earlier regarding heterogeneous populations, endogenous amenities, and

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

[31] Blomquist et al. (1988) found Alameda County, which contains Oakland, to be one of the best and Marin County to be one of the worst counties in the SF Bay Area. 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 there are high. As explained in Albouy (2008), the SF Bay Area in general fared badly in their article as they did not take into account federal taxes and non-housing costs-of-living.

sorting. These large differences are not exclusive to the central city: nearby suburbs in Long Island and New Jersey contain areas with a wide range of desirability.

The lowest quality of life is found in southwest Detroit City, MI, in the area containing the neighborhoods of Chadsey, Condon, and Vernor (see Figure 5C). Households are compensated with 25 percent (22 log points) of real income to live here (seen in Appendix Table A1). The Detroit MSA is relatively undesirable on average, though the suburbs of West Bloomfield and Birmingham are in the top 5 of PUMA rankings. 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 attractiveness.

Quality of life discrepancies in Atlanta, GA 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 percent more in rents, and endure commutes 10 percent longer to get the same wages. Willingness-to-pay in central cities is still 4 percent 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 5,000 residents per square mile, where willingness-to-pay is 5 percent above average. Some central-city areas have densities under 5,000, such as downtown Kansas City, MO: these areas offer a quality of life 3 percent below average. The results in Panel C formalize the finding that there appears to be about as much variation in willingness-to-pay within metro areas as across them. At each level, the standard deviation in values is almost 5 percent of gross income.[32] This variation is remarkable given that rents, and especially wages, vary less within MSAs than they do across them. This suggests that, geographi-

[32] 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.

cally, 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. They also lower rankings of large metro areas relative smaller ones, and also relative to non-metro areas. Without commuting, the San Francisco MSA would fall from number 2 to 4, behind the Santa Barbara and Salinas (Monterey Co.) MSAs in California, which offer lower wages and shorter commutes. Workers appear to be commuting for both higher wages and better amenities.

6 Predictors of Willingness-to-Pay

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 would be taken as causal. The regression coefficients would then be $\pi_k = -(\partial E/\partial Q)\left(\partial\tilde{Q}/\partial Z_k\right)/\bar{m}$, i.e., the fraction of gross income a household is willing to pay for one more unit of amenity k.[33] 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.[34] Thus, the dollar values we give are merely illustrative. More uniquely, we examine

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

[34] 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 nonlinearities in the hedonic equation.

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 minus the murder rate, which varies more within metros than across; such crimes are more common in central and dense areas. The same is true of bars and restaurants, which is our proxy of local entertainment. Public school revenues exhibit less variation within metros, much like local wage levels, which are likely the main source of cost differences. Nevertheless, these revenues are highest in the suburbs. As these artificial amenities are largely a product of local populations, they may proxy for the overall desirability of the populations themselves.

Table 6 reports the estimates from the amenity regressions. The eight variables explain 40 percent 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 that of Albouy (2008) for metro areas; the importance of climate is explored in greater depth in Albouy et al. (2013). The main observation here is that the coefficients for the temperature and slope variables are still relatively precise within metros and slightly larger than when predicted across metros. The sunshine estimate is understandably imprecise, mainly since we have fewer weather stations measuring it than metro areas. The coastal estimate however, remains more precise but becomes insignificant. This may be the result of how the variable is specified or measured, or perhaps residents in communities near the coasts find that "close is good enough," in the words of Schmidt and Courant (2006).

Although crime rates are available only at the county level, 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 $1,000 to $1,600 per household, depending on the specification.[35] The geographic coarseness of the crime measure suggests a downward bias, while murder's correlation with other crimes and other disamenities suggest 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 willingess-to-pay. Per 1,000, each establishment is associated with $170 rise in willingness-to-pay, or $170,000 total. This is roughly a third of the average revenue of a restaurant. This large number is unlikely to represent the value of having a bar or restaurant in the neighborhood, as they are located near other retail and entertainment establishments, in highly visited areas where residents can afford to eat out. The estimate would also cannot capture the value to residents outside the neighborhood.

The estimates reveal a strong association with school funding. This is despite the fact that local taxes are not controlled for. An increase in funding of $1,000 per student (or, since there are 0.9 students per household, $900 per household) is associated with a quality-of-life increase of $570. 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, households fund schools out of local taxes (see Brueckner 1982). Yet, these estimates have the same order of magnitude as the Cellini, Ferreira, and Rothstein (2010) estimate of the value of school facilities and the Black (1999), Bayer, Ferreira and McMillan (2007), and Caetano (2010) estimates of the willingness to pay for schools with higher test scores.

For the artificial amenities, the estimates from within metro areas is roughly similar to the overall estimates, except for crime, where the estimates are larger. Whether this is due to greater household sorting within metro areas deserves further investigation.

[35] It is worth noting that crime victims may not residents of the neighborhood where the crime occurred, although our measure is at the county level and counties are fairly large.

7 Conclusion

Although rankings of neighborhood quality are common in the popular literature, using a single index does require considerable simplification. Our index, based on the consumption "sacrifice" a typical household would make to live in different areas does seem to produce plausible results that many would find to be correlated to their own tastes. Analogously, it can be very useful to characterize policy preference from left to right, even though preferences over multidimensional policy issues will surely show some independence. While locally there may be differences in opinion on what makes for a good neighborhood, it does seem useful to have a standardized willingness-to-pay measure that may be used to compare neighborhoods in different metro areas.

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, where commutes are long, is higher than simpler measures imply. The place-of-work wage adjustment reveals that wages offered in central cities are as high as in the suburbs, implying that on average, central-city residents are not at a great disadvantage. Overall, the variation in local willingness-to-pay within metro areas appears to be as large as the variation across metro areas, often across nearby areas. In most places, such internal differences appear to have more to do with the population and artificial amenitiies, rather than the natural environment.

This analysis suggests interesting directions for future research. As we found that wages levels vary by much less than quality-of-life measures within metro areas, researchers might examine how households decide where to live based on the jobs available in different cities, and the clusters of neighborhoods that are accessible to them. Another natural extension would consider how willingness-to-pay for neighborhoods varies across groups, together with their propensity to live in those neighborhoods.

References

Albouy, David (2008), ”Are Big Cities Bad Places to Live: Estimating Quality of Life across Metropolitan Areas.” National Bureau of Economic Research Working Paper No. 14472, Cambridge, MA.

Alonso, William (1964), *Location and Land Use: Towards a General Theory of Land Rent*. Cambridge: Harvard University Press

Angrist, Joshua D. and Jorn-Steffen Pischke (2010) “The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics.” *Journal of Economic Perspectives*, 24(2), pp. 3-30.

Areavibes.com (2013) “Top 10 Cities - Best Place To Live 2013.” Retrieved February 2, 2014 from `http://www.areavibes.com/library/top-10-best-cities-to-live-2013/`.

Bajari, Pat and Matthew Kahn (2005) “Estimating Housing Demand With an Application to Explaining Racial Segregation in Cities.” *Journal of Business and Economic Statistics* 23(1): 20-33.

Baum-Snow, Nathaniel and Ronni Pavan (2012) ”Understanding the City Size Wage Gap” *Review of Economic Studies*, 79: 88-127.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan (2007) ”A Unified Framework for Measuring Preferences for Schools and Neighborhoods.” *Journal of Political Economy*, 115(4), pp. 588-638.

Bayer, Patrick and Christopher Timmins (2005) “On the Equilibrium Properties of Locational Sorting Models.” *Journal of Urban Economics*, 57(3), pp. 462-77.

Becker, Richard A., Lorraine Denby, Robert McGill, and Allan R. Wilks (1987) ”Analysis of Data From the *Places Rated Almanac*.” *The American Statistician*, 41, pp. 169-186.

Beeson, Patricia E. and Randall W. Eberts (1989) ”Identifying Productivity and Amenity Effects in Interurban Wage Differentials.” *The Review of Economics and Statistics,* 71, pp. 443-452.

Berger, Mark C., Glenn C. Blomquist, and Werner Waldner (1987) ”A Revealed-Preference Ranking of Quality of Life for Metropolitan Areas” *Social Science Quarterly*, 68, pp. 761-779.

Bieri, David S. Nicolai V. Kuminoff and Jaren C. Pope. (2013) ”National Expenditures on Local Amenities.” Unpublished manuscript. October 13.

Bishop, Kelly and Alvin Murphy (2011) ”Estimating the Willingness to Pay to Avoid Violent Crime: A Dynamic Approach” *American Economic Review Papers and Proceedings*, 101, pp. 625-629

Black, Dan, Natalia Kolesnikova and Lowell Taylor (2009) ”Earnings Functions When Wages and Prices Vary by Location” *Journal of Labor Economics*, 27(1), pp. 21-47.

Black, Sandra E. (1999) ”Do Better Schools Matter? Parental Valuation of Elementary Education” *Quarterly Journal of Economics*, 114, pp. 577-599.

Blomquist, Glenn C., Mark C. Berger, and John P. Hoehn (1988) ”New Estimates of Quality of Life in Urban Areas.” *American Economic Review*, 78, pp. 89-107.

Boustan, Leah Platt (2013) “Local Public Goods and the Demand for High-Income Municipalities.” *Journal of Urban Economics*, 76, pp. 71-82.

Brownstone, David and Kenneth A. Small. (2005) ”Valuing Time and Reliability: Assessing the Evidence from Road Pricing Demonstrations.” *Transportation Research Part A*, 39, pp. 279-293.

Brueckner, Jan K. (1982) ”A Test for Allocative Efficiency in the Local Public Sector” *Journal of Public Economics* 15, pp. 566-589.

Caetano, Gregorio (2010) “Identification and Estimation of Parental Valuation of School Quality in the U.S,” mimeo, University of Rochester.

Cellini, Stephanie, Fernando Ferreira and Jesse Rothstein (2010) ”The Value of School Facility Investments: Evidence from a Dynamic Regression Discontinuity Design.” *Quarterly Journal of Economics* 125, pp. 215-261.

Chen, Yu and Stuart Rosenthal (2008) ”Local Amenities and Life-Cycle Migration: Do People Move for Jobs or Fun?” *Journal of Urban Economics*, 64, pp. 519-537.

Colwell, Peter F., Carolyn A. Dehring and Geoffrey K. Turnbull (2002) “Recreation Demand and Residential Location.” *Journal of Urban Economics*, 51(3), pp. 418-428.

Combes, Pierre-Philippe, Gilles Duranton and Gobillon Laurent. (2008) ”Spatial Wage Disparities: Sorting Matters!” *Journal of Urban Economics* 63(2), pp. 723-742.

Cutler, David M. and Edward L. Glaeser. (1997) ”Are Ghettos Good or Bad?” *The Quarterly Journal of Economics* 112(3), pp. 827-872.

Davis, Lucas (2004) ”The Effect of Health Risk on Houisng Values: Evidence from a Cancer Cluster.” *American Economic Review*, 94(5), pp. 1693-1704.

Epple, Dennis and Holger Sieg (1999) ”Estimating Equilibrium Models of Locational Sorting.” *Journal of Political Economy*, 107(4), pp. 645-681.

Feenberg, Daniel R. and Elisabeth Coutts (1993), ”An Introduction to the TAXSIM Model.” *Journal of Policy Analysis and Management*, 12, pp. 189-194.

Ferreira, Fernando and Joseph Gyourko (2011) ”Anatomy of the Beginning of the Housing Boom: U.S. Neighborhoods and Metropolitan Areas, 1993-2009.” National Bureau of Economic Research Working Paper No. 17374, Cambridge, MA.

Fu, Shihe, and Stephen L. Ross (2013) ”Wage Premia in Employment Clusters: Agglomeration or Worker Heterogeneity?” *Journal of Labor Economic*s, 31: 271-304.

Gabriel, Stuart A., Joe P. Mattey, and William L. Wascher (2003) ”Compensating differentials and evolution in the quality-of-life among U.S. states” *Regional Science and Urban Economics*, 33, pp. 619-649.

Gabriel, Stuart A. and Stuart S. Rosenthal (1996) ”Commutes, Neighborhood Effects, and Earnings: An Analysis of Racial Discrimination and Compensating Differentials” *Journal of Urban Economics*, 40, pp. 61-83.

Gabriel, Stuart A. and Stuart S. Rosenthal (2004) ”Quality of the Business Environment versus Quality of Life: Do Firms and Households Like the Same Cities?” *The Review of Economics and Statistics*, 86, pp.548-444.

Gautier, Pieter A., Arjen Siegmann, and Aico Van Vuuren (2009) “Terrorism and attitudes towards minorities: The effect of the Theo van Gogh murder on house prices in Amsterdam.” *Journal of Urban Economics*, 65, pp. 113-126.

Glaeser, Edward L. and David Maré (2001) ”Cities and Skills.” *Journal of Labor Economics,* 19, pp. 316-342.

Gyourko, Joseph and Joseph Tracy (1989) ”The Importance of Local Fiscal Conditions in Analyzing Local Labor Markets.” *Journal of Political Economy,* 97, pp. 1208-31.

Gyourko, Joseph and Joseph Tracy (1991) ”The Structure of Local Public Finance and the Quality of Life.” *Journal of Political Economy*, 99, pp. 774-806.

Gyourko, Joseph, Matthew Kahn and Joseph Tracy (1999) ”Quality of Life and Environmental Comparisons.” in E. Mills and P. Cheshire, eds. *Handbook of Regional and Urban Economics,* Vol. 3. Amsterdam: North Holland.

Gyourko, Joseph, Christopher Mayer and Todd Sinai (2013) “Superstar Cities” *American Economic Journal: Economic Policy*. 5(4), pp. 167-99

Hamermesh, Daniel (1999) “Crime and the Timing of Work.” *Journal of Urban Economics*, 45(2), pp. 311-330.

Hoehn, John P., Mark C. Berger, and Glenn C. Blomquist (1987) ”A Hedonic Model of Interregional Wages, Rents, and Amenity Values.” *Journal of Regional Science*, 27, pp. 605-620.

Ioannides, Yannis M. (2004) ”Neighborhood income distributions.” *Journal of Urban Economics*, 56, pp. 435-457.

Kahneman, Daniel, and Alan Krueger (2006) ”Developments in the Measurement of Subjective Well-Being” *Journal of Economic Perspectives,* 20, pp. 3-24.

Kim, Dongsoo, Feng Liu, and Anthony Yezer (2009) “Do inter-city differences in intra-city wage differentials have any interesting implications?” *Journal of Urban Economics*, 66(3), pp. 151-232.

Krueger, Alan B. (1999), ”Measuring Labor’s Share.” *American Economic Review,* 89, pp. 45-51.

Kuminoff, Nicolai, and Jaren Pope. (2013) ”Do ’Capitalization’ Effects for Public Goods Reveal the Public’s Willingness to Pay?” *International Economic Review*.

Kuminoff, Nicolai, V. Kerry Smith, and Christopher Timmins (2013) ”The New Economics of Equilibrium Sorting and Policy Evaluation Using Housing Markets.” *Journal of Economic Literature* 51(4), pp. 1007-1062.

Lee, Sanghoon and Jeffrey Lin (2013) ”Natural Amenities, Neighborhood Dynamics, and Persistence in the Spatial Distribution of Income.” Federal Reserve Bank of Philadelphia Working Paper No. 13-48. Philadelphia, PA.

Linden, Leigh and Jonah E. Rockoff (2008) “Estimates of the Impact of Crime Risk on Property Values from Megan’s Laws.” *American Economic Review* 98(3), pp. 1103-1127.

Malpezzi, Stephen, Gregory H. Chun, and Richard K. Green (1998) ”New Place-to-Place Housing Price Indexes for U.S. Metropolitan Areas, and Their Determinants.” *Real Estate Economics,* 26, pp. 235-274.

McDuff, DeForest (2011) “Demand Substitution Across US Cities: Observable Similarity and Home Price Correlation.” *Journal of Urban Economics* 70(1), pp. 1-14.

McMillen, Daniel P. and Larry D. Singell Jr. (1992) ”Work Location, Residence Location, and the Intraurban Wage Gradient.” *Journal of Urban Economics*, 32, pp. 195-213.

Mills, Edwin S. (1967), ”An Aggregative Model of Resource Allocation in a Metropolitan Area”, *American Economic Review Proceedings.* **57** 197-210.

Muth, Richard .F. (1969) *Cities and Housing: The Spatial Pattern of Urban Land Use.* Chicago: Univ of Chicago Press.

Nevo, Avia and Michael D. Whinston (2010) “Taking the Dogma out of Econometrics: Structural Modleing and Credible Inference.” *Journal of Economic Perspectives*, 24(2), pp. 69-82.

Oates, Wallace E. (1969) ”The Effects of Property Taxes and Local Public Spending on Property Values: An Empirical Study of Tax Capitalization and the Tiebout Hypothesis.” *Journal of Political Economy,* 77, pp. 957-71.

Office of Management and Budget. (2000) ”Standards for Defining Metropolitan and Micropolitan Statistical Areas: Notice.”

Peiser, Richard B. and Lawrence B. Smith (1985) ”Homeownership Returns, Tenure Choice and Inflation.” *American Real Estate and Urban Economics Journal*, 13, pp. 343-60.

Petitte, Ryan A. and Stephen L. Ross (1999) ”Commutes, Neighborhood Effects, and Compensating Differentials: Revisited.” *Journal of Urban Economics*, 46, pp. 1-24.

Pollakowski, Henry O. (2003) ”Who Really Benefits from New York City’s Rent Regulation System?” *Civic Report*, 34, pp. 1-27.

Pope, Jaren C. (2008) “Fear of Crime and Housing Prices: Household Reactions to Sex Offender Registries.” *Journal of Urban Economics*, 64, pp. 601-614.

Schmidt, Lucie and Paul Courant (2006) "Sometimes Close is Good Enough: The Value of Nearby Environmental Amenities." *Journal of Regional Science*, 46(5), pp. 931-951.

Roback, Jennifer (1980) "The Value of Local Urban Amenities: Theory and Measurement." Ph.D. dissertation, University of Rochester.

Roback, Jennifer (1982) "Wages, Rents, and the Quality of Life." *Journal of Political Economy*, 90, pp. 1257-1278.

Roback, Jennifer (1988) "Wages, Rents, and Amenities: Differences among Workers and Regions." *Economic Inquiry,* 26, pp. 23-41.

Rosenthal, Stuart, and William Strange (2001) "The Determinants of Agglomeration." *Journal of Urban Economics*, 50, pp. 191–229.

Ruggles, Steven; Matthew Sobek; Trent Alexander; Catherine A. Fitch; Ronald Goeken; Patricia Kelly Hall; Miriam King; and Chad Ronnander. (2004) *Integrated Public Use Microdata Series: Version 3.0*. Minneapolis: Minnesota Population Center.

Rosen, Sherwin (1979) "Wages-based Indexes of Urban Quality of Life." in P. Mieszkowski and M. Straszheim, eds. *Current Issues in Urban Economics,* Baltimore: John Hopkins Univ. Press.

Rosenthal, Stuart and Amanda Ross (2010) "Violent Crime, Entrepreneurship, and Cities." *Journal of Urban Economics* 67, pp. 135-149.

Savageau, David (1999) *Places Rated Almanac.* Foster City, CA: IDG Books Worldwide.

Silver, Nate (2010) "The Most Livable Neighborhoods in New York: A quantitative index of the 50 most satisfying places to live." *New York Magazine*, April 11. http://nymag.com/realestate/neighborhoods/2010/65374/.

Small, Kenneth A. and E. T. Verhoef (2007) *The Economics of Urban Transportation*, New York: Routledge.

Small, Kenneth A., Clifford Winston, and Jia Yan (2005) ”Uncovering the Distribution of Motorists’ Preferences for Travel Time and Reliability.” *Econometrica*, 73, pp. 1367-1382.

Streetadvisor.com (2013) “Best Cities in New York City.” Retrieved February 2, 2014 from `http://www.streetadvisor.com/search/cities-in-new-york-city-new-york`.

Straszheim, Mahlon R. (1984) ”Urban Agglomeration Effects and Employment and Wage Gradients.” *Journal of Urban Economics,* 16, pp. 187-207.

Tiebout, Charles M. (1956) ”A Pure Theory of Local Expenditures.” *Journal of Political Economy.* 64 pp. 416-424.

Timothy, Darren and William C. Wheaton. (2001)”Intra-Urban Wage Variation, Employment Location, and Commuting Times.” *Journal of Urban Economics*, 50, pp. 338-366.

Turnbull, Geoffrey K. (1992) “Location, Housing, and Leisure Demand under Local Employment.” *Land Economics*, 68, pp. 62-71.

Turnbull, Geoffey K. (1995) *Urban Consumer Theory*. Washington D.C.: Urban Institute Press.

Yinger, John (2014) “Hedonic Markets and Sorting Equilibria: Bid-functions for Public Services and Neighborhood Amenities.”

Zax, Jeffrey S. (1991) ”Compensation for Commutes in Labor and Housing Markets.” *Journal of Urban Economics*, 30, pp. 192-207.

TABLE 1: RENT, WAGE, COMMUTING-COST, AND QUALITY-OF-LIFE DIFFERENTIALS ACROSS THE U.S., 2000

Differential		Rents/Hous. Cost		Wage			Commuting		Quality of Life	
	Population	Location Index or "Rent"	Compo-sition or "Quality"	Index by Work-place	Index by Resi-dence	Compo-sition or "Skill"	Index of Full Cost	Time Cost 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	0.060	-0.100	0.031	0.010	-0.044	-0.003	-0.010	-0.001	0.013
Suburban (in Metro)	141,255,868	0.083	0.057	0.032	0.051	0.034	0.006	0.055	0.016	0.000
Non-Metropolitan Areas	54,764,922	-0.329	0.009	-0.141	-0.158	-0.021	-0.013	-0.141	-0.042	-0.021
Panel B: By Residential Population Density										
>5,000 per square mile	75,957,757	0.261	-0.141	0.108	0.085	-0.061	0.006	0.106	0.031	0.036
1,000-5,000 per square mile	126,073,690	0.006	0.061	0.002	0.019	0.040	-0.001	-0.029	0.000	-0.008
<1,000 per square mile	79,390,459	-0.274	0.039	-0.113	-0.119	-0.005	-0.005	-0.065	-0.032	-0.023
Panel C:Standard Deviations										
All PUMAs		0.348	0.146	0.127	0.145	0.104	0.019	0.220	0.068	0.056
Across Metropolitan Areas		0.302	0.071	0.123	0.130	0.047	0.015	0.176	0.051	0.043
Within Metropolitan Areas		0.173	0.128	0.033	0.065	0.093	0.012	0.132	0.046	0.037
Fraction of Variance Within		*0.247*	*0.769*	*0.068*	*0.201*	*0.800*	*0.399*	*0.360*	*0.458*	*0.437*

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 indicitor 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 to 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 equation (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 a distinct metropolitan area, although the results do not change substantially if they are excluded. See text for greater detail.

TABLE 2: RENT, WAGE, COMMUTING-COST, AND QUALITY-OF-LIFE DIFFERENTIALS WITHIN MANHATTAN AND SAN FRANCISCO, 2000

		Rents/Hous. Cost		Wage			Commuting		Quality of Life		
Area Name	Population (1)	Location Index or "Rent" (2)	Compo-sition or "Quality" (3)	Index by Work-place (4)	Index by Resi-dence (5)	Compo-sition or "Skill" (6)	Index of Full Cost (7)	Time Cost Only (8)	Workpla. Adj. Index (9)	Simple (not used) (10)	QOL rank from (9) (11)
New York Co., NY (Manhattan)	*1,537,195*	*0.621*	*-0.264*	*0.270*	*0.287*	*0.004*	*-0.006*	*0.114*	*0.047*	*0.045*	*72*
Upper East Side	217,063	1.327	-0.520	0.269	0.479	0.224	-0.004	0.155	0.265	0.123	5
Stuy Town/Turtle Bay	143,441	1.256	-0.615	0.266	0.431	0.195	-0.019	-0.017	0.230	0.119	11
Greeewich Vlg./Fin. District	125,567	1.230	-0.540	0.268	0.409	0.186	-0.020	-0.084	0.220	0.126	15
Upper West Side	192,213	1.132	-0.556	0.269	0.458	0.208	-0.003	0.138	0.207	0.072	23
Midtown West/Chelsea	122,241	1.027	-0.586	0.267	0.415	0.125	-0.025	-0.123	0.154	0.056	64
Washington Hts./Inwood	216,234	0.275	-0.561	0.223	0.049	-0.221	0.021	0.496	-0.007	0.060	976
Lower E. Side/Chinatown	166,379	0.379	-0.518	0.249	0.070	-0.133	-0.007	0.148	-0.016	0.037	1118
Morningside Hts./Hamilton Hts.	129,533	0.264	-0.497	0.232	0.113	-0.088	0.008	0.320	-0.027	0.024	1250
Central Harlem	109,091	-0.046	-0.446	0.235	0.204	-0.185	0.010	0.294	-0.121	-0.116	2037
East Harlem	115,433	-0.060	-0.461	0.233	0.138	-0.198	0.011	0.348	-0.125	-0.087	2042
San Francisco City & Co., CA	*776,733*	*0.934*	*-0.176*	*0.265*	*0.245*	*-0.016*	*-0.001*	*0.082*	*0.151*	*0.161*	*5*
Ingleside	105,194	1.116	-0.148	0.258	0.256	0.008	0.018	0.259	0.229	0.198	13
Sunset	105,532	1.077	-0.203	0.266	0.228	0.051	0.023	0.347	0.217	0.194	17
Buena Vista/Central/Bernal Hts.	109,355	1.055	-0.272	0.264	0.254	0.077	0.007	0.163	0.196	0.161	29
Marina/N.E. SF	107,285	1.042	-0.423	0.264	0.385	0.088	-0.002	0.099	0.183	0.090	33
Richmond/W. Addition	136,975	0.976	-0.284	0.262	0.265	0.054	0.012	0.215	0.178	0.132	38
S. Bayshore/S. Central	105,338	0.662	-0.168	0.245	0.164	-0.200	0.014	0.222	0.093	0.106	199
Downtown/SOMA/Mission	107,054	0.680	-0.585	0.254	0.177	-0.110	-0.015	-0.039	0.065	0.077	319

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-broughs of Manhattan and by ln(1.19) in San Francisco. Quality-of-Life Rankings are out of 2071 PUMAs. See Table 1 for more.

TABLE 3: HOUSEHOLD CHARACETRISTICS WITHIN, ACROSS, AND OUTSIDE U.S. METROPOLITAN AREA

	Under 18 (1)	Over 65 (2)	Married (3)	House-hold size (4)	In Labor Force (5)	College Degree (6)	Race: Black (7)	Immi-grant (8)
Panel A: Central City, Suburban, or non-Metropolitan Area								
Central City (in Metro)	0.27	0.11	0.37	2.58	0.49	0.37	0.20	0.18
Suburban (in Metro)	0.28	0.12	0.45	2.68	0.51	0.38	0.09	0.12
Non-Metropolitan Areas	0.28	0.14	0.46	2.52	0.48	0.22	0.08	0.04
Panel B: By Residential Population Density								
>5,000 per square mile	0.27	0.11	0.37	2.71	0.49	0.38	0.19	0.26
1,000-5,000 per square mile	0.28	0.12	0.44	2.60	0.51	0.39	0.10	0.10
<1,000 per square mile	0.28	0.13	0.47	2.56	0.49	0.24	0.08	0.04
Panel C:Standard Deviations								
All PUMAs	0.041	0.041	0.066	0.326	0.055	0.187	0.172	0.127
Across Metropolitan Areas	0.023	0.028	0.026	0.199	0.035	0.102	0.095	0.101
Within Metropolitan Areas	0.035	0.029	0.060	0.259	0.042	0.156	0.143	0.077
Fraction of Variance Within	*0.729*	*0.500*	*0.826*	*0.631*	*0.583*	*0.696*	*0.691*	*0.368*

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

TABLE 3: RENT, WAGE, COMMUTING-COST, AND QUALITY-OF-LIFE DIFFERENTIALS FOR FOUR LEVELS OF GEOGRAPHY WITHIN FIVE METROPOLITAN AREAS, 2000

Area Name	Unit of Geog-raphy	Population (1)	Housing Cost Index (2)	Wage by Work-place (3)	Full Commute Cost (4)	Quality of Life Adj. (5)	QOL Rank in Geog. Unit (6)
Honolulu, HI	**MSA**	**876,156**	**0.589**	**0.014**	**0.002**	**0.174**	**1**
East Oahu/Waialae-Kahala	PUMA	102,724	0.947	0.014	0.005	0.286	1
Kaneohe/Kailua	PUMA	117,994	0.749	0.013	0.010	0.231	10
Pearl City/Waimalu/W. Honolulu	PUMA	144,481	0.626	0.013	-0.008	0.176	39
Waipahu/Mililani/Ewa	PUMA	178,534	0.459	0.015	0.026	0.159	57
Waikiki/Alo Maoni/Kapiolani	PUMA	109,509	0.621	0.015	-0.027	0.155	62
Downtown Honolulu	PUMA	109354	0.447	0.015	-0.016	0.112	127
West Oahu/Midway Islands	PUMA	113560	0.360	0.017	0.009	0.110	134
San Francisco-Oakland-San Jose, CA	**MSA**	**7,039,362**	**0.784**	**0.240**	**0.012**	**0.130**	**2**
San Francisco, CA	PMSA	1,731,183	1.022	0.264	0.009	0.188	1
Marin Co.	*County*	*247,289*	*1.104*	*0.228*	*0.018*	*0.240*	*1*
San Rafael/Sausalito/Mill Valley	PUMA	146,373	1.208	0.230	0.014	0.267	4
Novato/Lucas Valley/Point Reyes	PUMA	100,916	0.954	0.224	0.023	0.201	28
San Mateo Co.	*County*	*707,161*	*1.078*	*0.281*	*0.006*	*0.193*	*2*
San Francisco Co.	*County*	*776,733*	*0.946*	*0.259*	*0.008*	*0.166*	*4*
Santa Cruz-Watsonville, CA	PMSA	255,602	0.782	0.162	0.007	0.164	3
San Jose, CA	PMSA	1,682,585	0.956	0.300	0.006	0.147	4
Santa Rosa, CA	PMSA	458,614	0.566	0.132	0.003	0.110	7
Oakland, CA	PMSA	2,392,557	0.625	0.230	0.021	0.096	11
Vallejo-Fairfield-Napa, CA	PMSA	518,821	0.355	0.152	0.010	0.042	45
New York, N. NJ, Long Is., NY-NJ-CT-PA	**MSA**	**25,036,899**	**0.416**	**0.197**	**0.021**	**0.048**	**22**
Nassau-Suffolk, NY	PMSA	2,753,913	0.528	0.182	0.030	0.099	9
Bergen-Passaic, NJ	PMSA	1,373,167	0.455	0.199	0.028	0.067	23
New York, NY	PMSA	9,314,235	0.444	0.210	0.020	0.050	37
Westchester Co.	*County*	*923,459*	*0.653*	*0.210*	*0.025*	*0.119*	*17*
Putnam Co.	*County*	*95,745*	*0.469*	*0.189*	*0.054*	*0.102*	*28*
New York Co. (Manhattan)	*County*	*1,537,195*	*0.723*	*0.252*	*-0.002*	*0.092*	*42*
Queens Co.	*County*	*2,229,379*	*0.486*	*0.189*	*0.038*	*0.092*	*43*
Richmond Co. (Staten Island)	*County*	*443,728*	*0.438*	*0.189*	*0.051*	*0.090*	*55*
Rockland Co.	*County*	*286,753*	*0.479*	*0.179*	*0.024*	*0.080*	*68*
Kings Co. (Brooklyn)	*County*	*2,465,326*	*0.345*	*0.182*	*0.033*	*0.047*	*171*
Bronx Co.	*County*	*1,332,650*	*0.160*	*0.189*	*0.032*	*-0.015*	*758*
Stamford-Norwalk, CT	PMSA	882,567	0.582	0.268	0.010	0.053	34
Danbury, CT	PMSA	1,064,760	0.516	0.243	0.010	0.045	41
Monmouth-Ocean, NJ	PMSA	1,126,217	0.268	0.168	0.034	0.031	60
Middlesex-Somerset-Hunterdon, NJ	PMSA	1,169,641	0.384	0.220	0.024	0.031	61
Newark, NJ	PMSA	2,032,989	0.375	0.214	0.019	0.026	69
Newburgh, NY-PA	PMSA	387,669	0.091	0.076	0.030	0.019	82
Dutchess County, NY	PMSA	280,150	0.155	0.102	0.020	0.016	89
Bridgeport, CT	PMSA	1,706,575	0.380	0.212	0.004	0.014	91
Jersey City, NJ	PMSA	608,975	0.322	0.233	0.020	0.001	117
Waterbury, CT	PMSA	1,006,201	0.189	0.139	-0.002	-0.014	160
New Haven-Meriden, CT	PMSA	979,079	0.192	0.141	-0.003	-0.015	162
Trenton, NJ	PMSA	350,761	0.231	0.194	0.004	-0.022	179

TABLE 3: WAGE, HOUSING-COST, COMMUTING-COST, AND QUALITY-OF-LIFE DIFFERENTIALS FOR DIFFERENT LEVELS OF GEOGRAPHY WITHIN FIVE METROPOLITAN AREAS, 2000

Area Name	Unit of Geog-raphy	Population (1)	Housing Cost Index (2)	Wage by Work-place (3)	Full Commute Cost (4)	Quality of Life Adj. (5)	QOL Rank in Geog. Unit (6)
Atlanta, GA	**MSA**	**4,112,198**	**0.023**	**0.060**	**0.018**	**-0.005**	**95**
DeKalb Co.	*County*	*665,865*	*0.129*	*0.074*	*0.018*	*0.020*	*302*
Cobb Co.	*County*	*607,751*	*0.091*	*0.076*	*0.022*	*0.012*	*389*
Fulton Co.	*County*	*816,006*	*0.159*	*0.091*	*0.006*	*0.009*	*425*
Forsyth & Pickens Cos.	*County*	*98,407*	*0.015*	*0.042*	*0.023*	*0.006*	*440*
Cherokee Co.	*County*	*141,903*	*-0.014*	*0.043*	*0.030*	*0.004*	*464*
Gwinnett Co.	*County*	*588,448*	*0.023*	*0.067*	*0.023*	*-0.004*	*579*
Coweta, Fayette, & Spalding Cos.	*County*	*89,215*	*-0.114*	*0.014*	*0.016*	*-0.026*	*974*
Carroll & Douglas Cos.	*County*	*92,174*	*-0.193*	*-0.004*	*0.021*	*-0.036*	*1185*
Henry	*County*	*119,341*	*-0.154*	*0.042*	*0.029*	*-0.039*	*1267*
Bartow & Paulding Cos.	*County*	*76,019*	*-0.221*	*0.014*	*0.036*	*-0.039*	*1281*
Newton & Rockdale Cos.	*County*	*62,001*	*-0.164*	*0.019*	*0.017*	*-0.042*	*1362*
Barrow & Walton Cos.	*County*	*46,144*	*-0.219*	*0.007*	*0.026*	*-0.044*	*1458*
Clayton Co.	*County*	*236,517*	*-0.116*	*0.054*	*0.012*	*-0.050*	*1627*
Detroit-Ann Arbor-Flint, MI	**MSA**	**5,456,428**	**0.028**	**0.115**	**0.008**	**-0.041**	**205**
Ann Arbor, MI	PMSA	578,736	0.138	0.077	0.003	0.007	106
Livingston Co.	*County*	*156,951*	*0.194*	*0.100*	*0.025*	*0.034*	*230*
Washtenaw Co.	*County*	*322,895*	*0.208*	*0.093*	*-0.007*	*0.010*	*412*
Ann Arbor	PUMA	114,024	0.346	0.084	-0.022	0.041	485
Ypsilanti/Saline/Pittsfield Twp.	PUMA	208,871	0.133	0.099	0.002	-0.007	988
Lenawee Co.	*County*	*98,890*	*-0.180*	*-0.013*	*0.001*	*-0.047*	*1523*
Detroit, MI	PMSA	4,441,551	0.039	0.126	0.009	-0.042	257
Oakland Co.	*County*	*1,194,156*	*0.268*	*0.144*	*0.012*	*0.022*	*287*
St. Clair & Lapeer Co.	*County*	*87,904*	*-0.036*	*0.044*	*0.021*	*-0.012*	*690*
Macomb Co.	*County*	*788,149*	*0.099*	*0.129*	*0.014*	*-0.020*	*878*
Monroe Co.	*County*	*145,945*	*-0.023*	*0.069*	*0.008*	*-0.034*	*1149*
Wayne Co.	*County*	*2,061,162*	*-0.103*	*0.129*	*0.004*	*-0.092*	*2899*
Flint, MI	PMSA	436,141	-0.226	0.057	0.003	-0.094	375

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 constains 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. There are 3081 counties, 2071 PUMAs, 373 PMSA or PMSA-equivalents, and 327 MSAs or MSA-equivalents, in the sample. See Table 1 for greater detail.

TABLE 5: SELECTED AMENITIES WITHIN, ACROSS, AND OUTSIDE U.S. METROPOLITAN AREAS, 2000

	Annual Heating Degree Days	Annual Cooling Degree Days	Annual Sunshine Percent Possible	Inverse Distance to Coast	Average Slope of Land	Murder Rate per 1,000	Rest-aurants and Bars per 1,000	Public School Revenues per Student
	(1)	(2)	(3)	(4)	(4)	(5)	(6)	(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								
>5,000 per square mile	3.71	1.28	0.63	0.19	0.01	0.09	1.80	0.88
1,000-5,000 per square mile	4.49	1.33	0.60	0.05	0.02	0.05	1.73	0.82
<1,000 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*

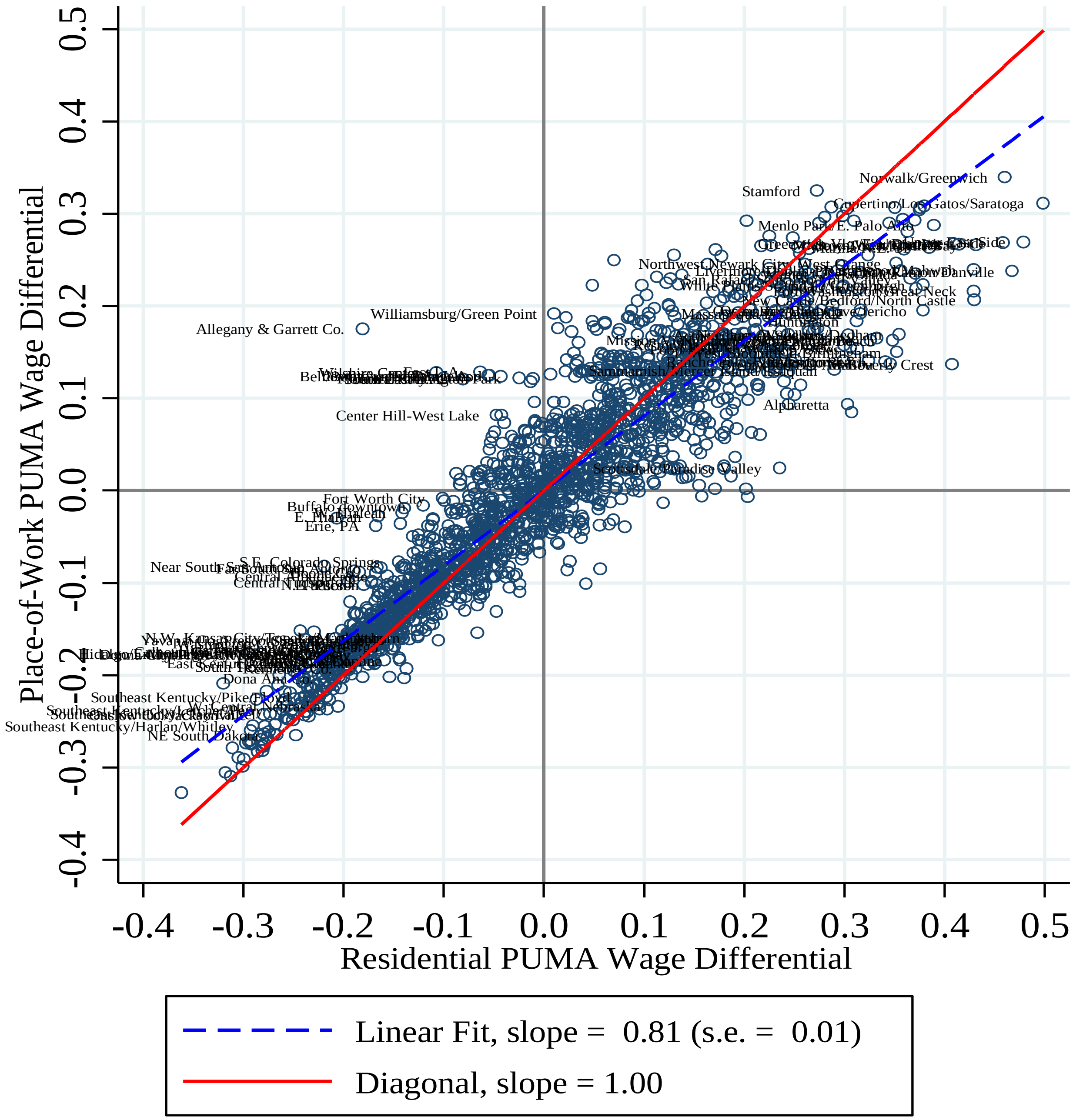
data are taken from sources described in the appendix. Murder rate, restaurants and bars and public school revenues are at the county level. Cooling and heating degree days are from a 65F base. Revenues per student are measured in $10,000 units. See Table 1 and text for greater detail.

TABLE 6: AMENITY PREDICTORS OF LOCAL WILLINGNESS-TO-PAY

Dependent Variables	All QOL by PUMA (1)	Within MSA Adj QOL (2)
Minus 1000s of Heating Degree Days, 65F base	0.019***	0.031***
(mean = 4.50, sd = 2.25)	(0.001)	(0.004)
Minus 1000s of Cooling Degree Days, 65F base	0.036***	0.054***
(mean = 1.25, sd = 0.91)	(0.002)	(0.007)
Sunshine, percent possible	0.121***	-0.084
(mean = 0.060, sd = 0.078)	(0.019)	(0.089)
Inverse distance to coast	0.093***	0.013
(mean = 0.71, sd =0.14)	(0.016)	(0.017)
Average Slope of Land, in percent	0.576***	0.859***
(mean = 1.80, sd = 2.22)	(0.060)	(0.093)
Minus Murder Rate per 1,000	0.144***	0.252***
(mean = 0.05, sd = 0.053)	(0.030)	(0.028)
Restaurants and Bars per Thousand	0.026***	0.023***
(mean = 1.71, sd = 0.28)	(0.003)	(0.004)
Public School Revenues per Student, $10,000s	0.084***	0.071**
(mean = 0.50, sd = 0.13)	(0.009)	(0.020)
R-squared	0.41	0.64
Number of Observations	1948	1948

Robust standard errors shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Regressions weighted by population. Variables are described in the Appendix, including Appendix Table A6.

Figure 1: Wages Estimated by Workplace or by Residence



Unit of observation is the residential PUMA.

Figure 2A: Residential Rents (Gross or Imputed) across the United States, 2000

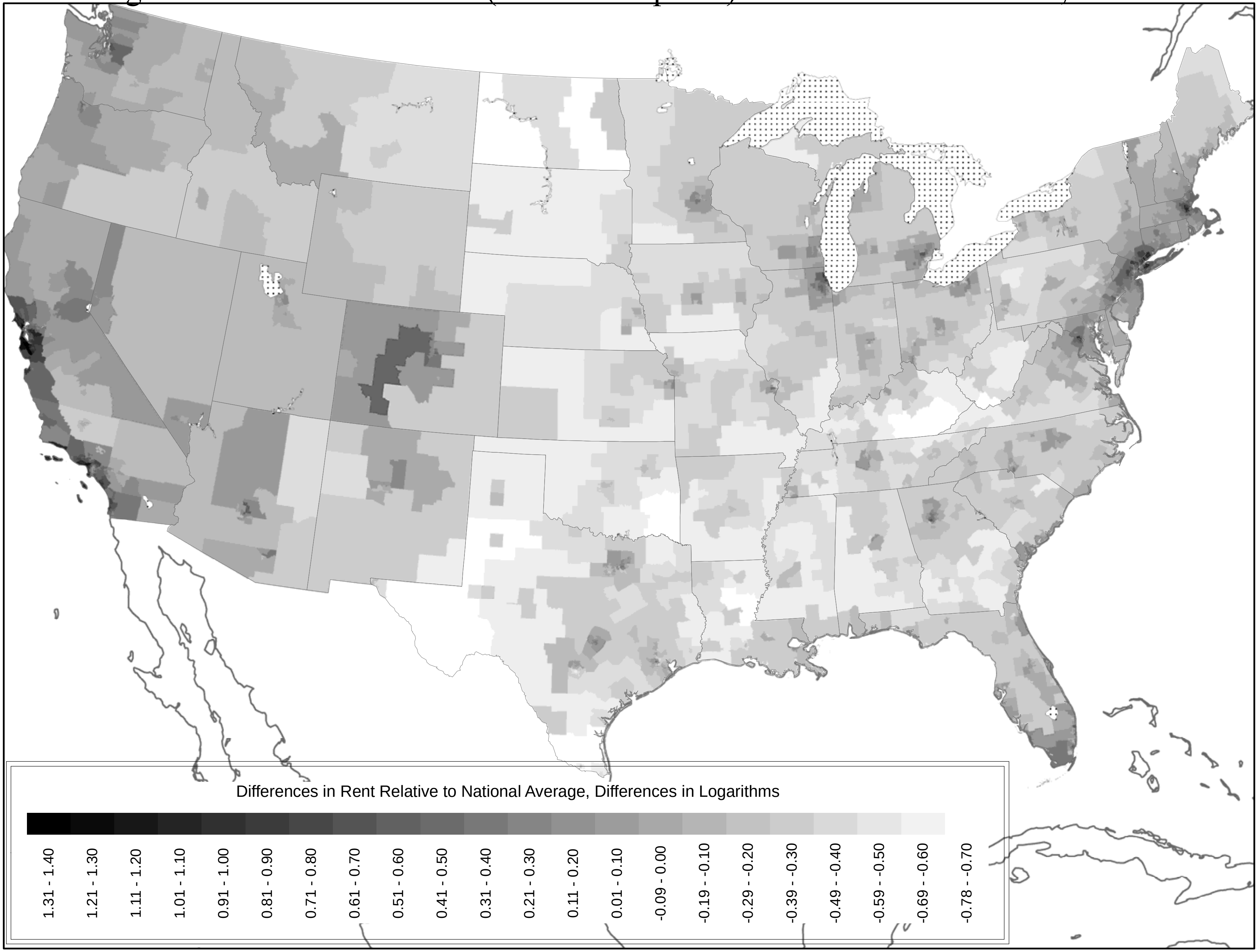


Figure 2B: Wage Levels by Workplace across the United States, 2000

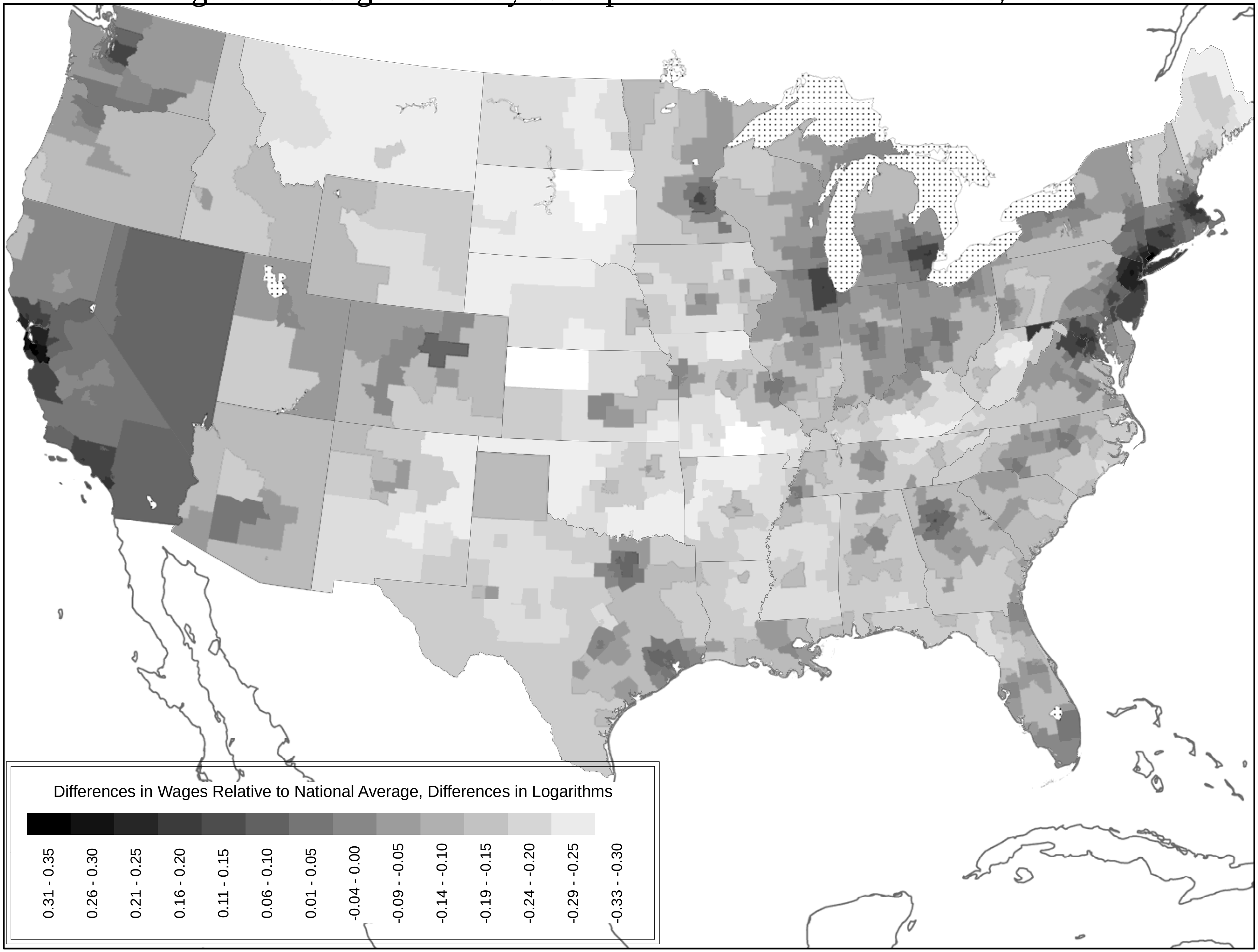


Figure 2C: Commuting Costs across the United States, 2000

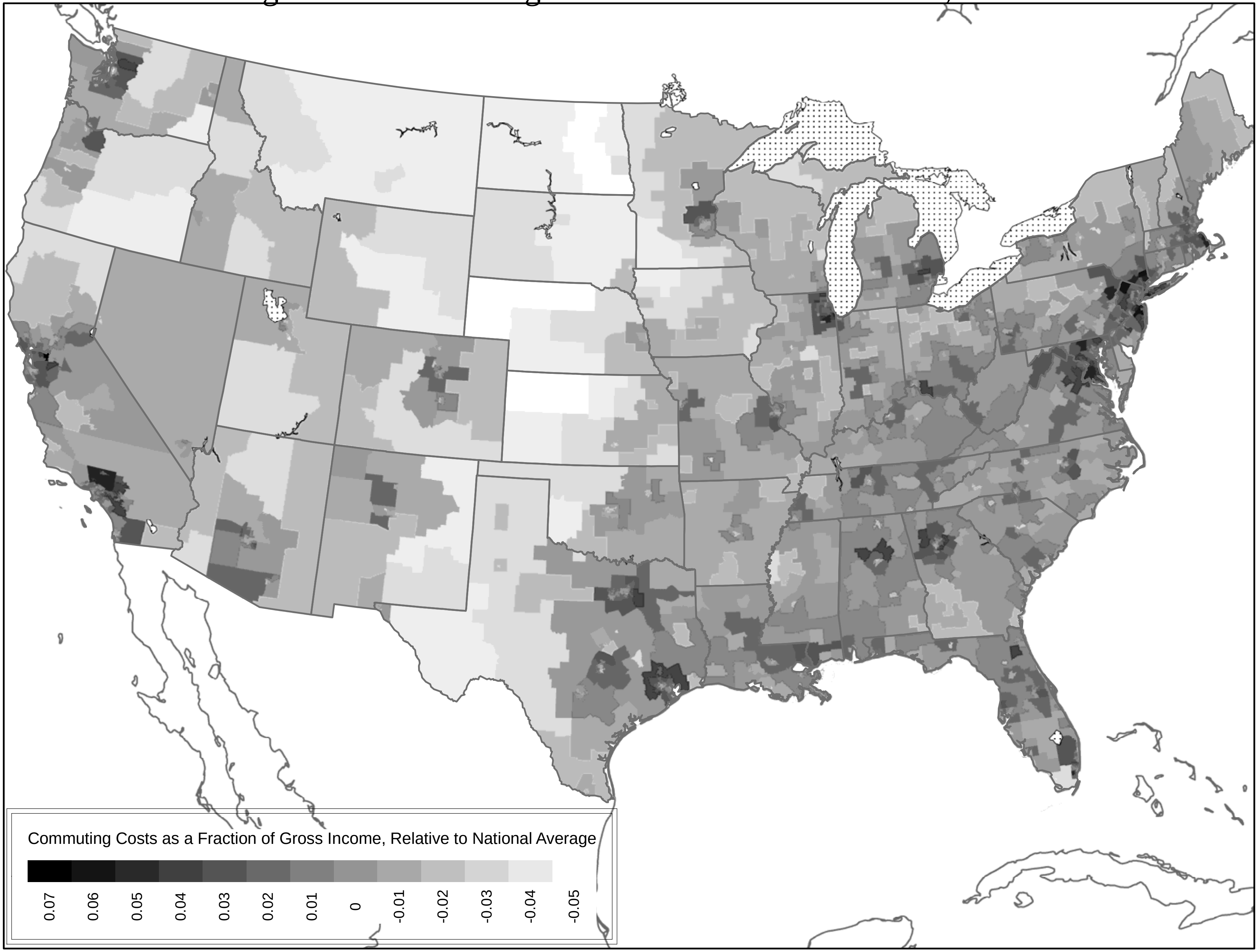
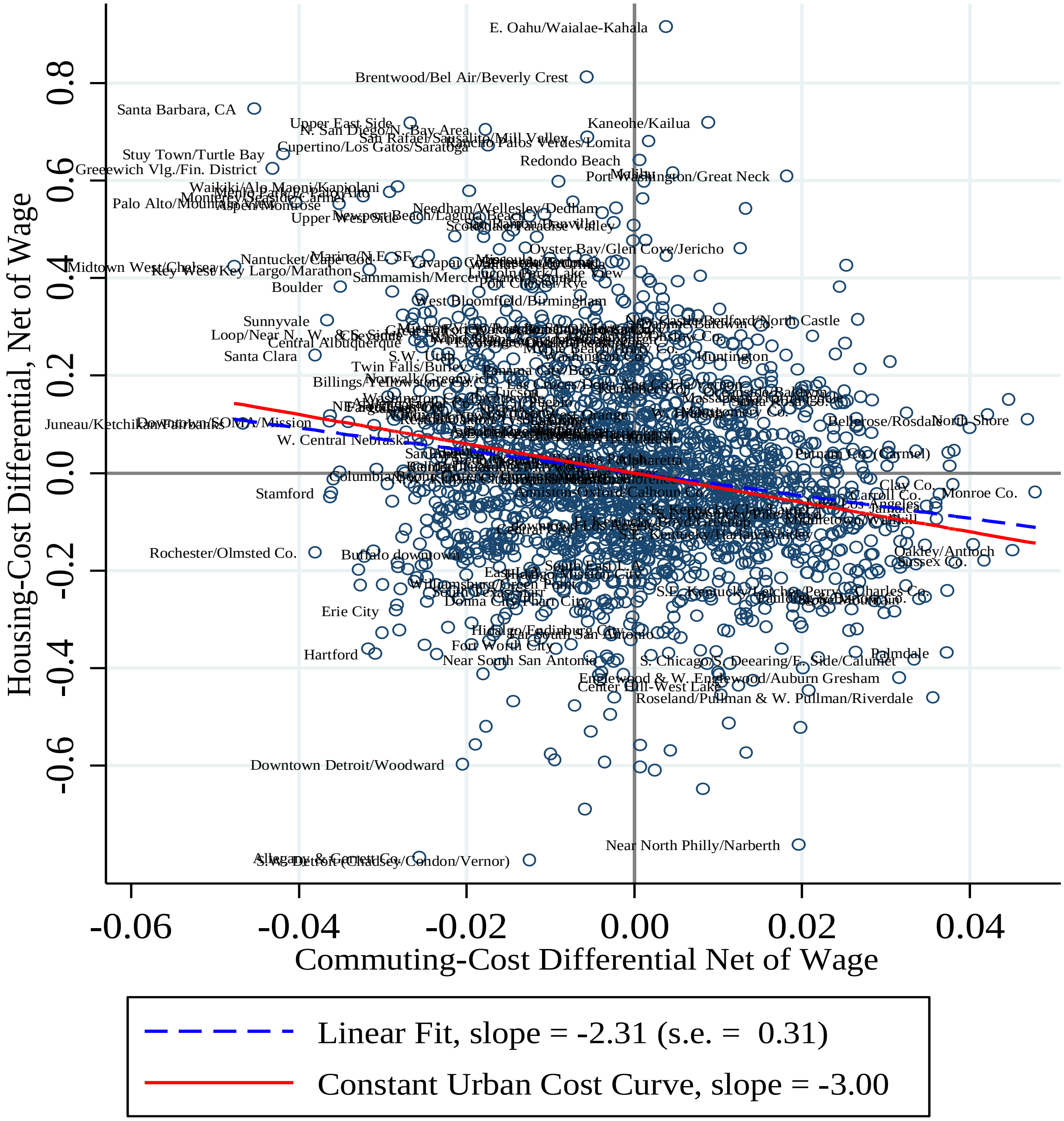


Figure 3: Housing and Commuting Costs



Housing and commuting-cost differentials are residuals from separate regressions on workplace wage levels. Nome/Barrow/Other Alaska left out of scatter plot.

Figure 4: Quality of Life across the United States, 2000

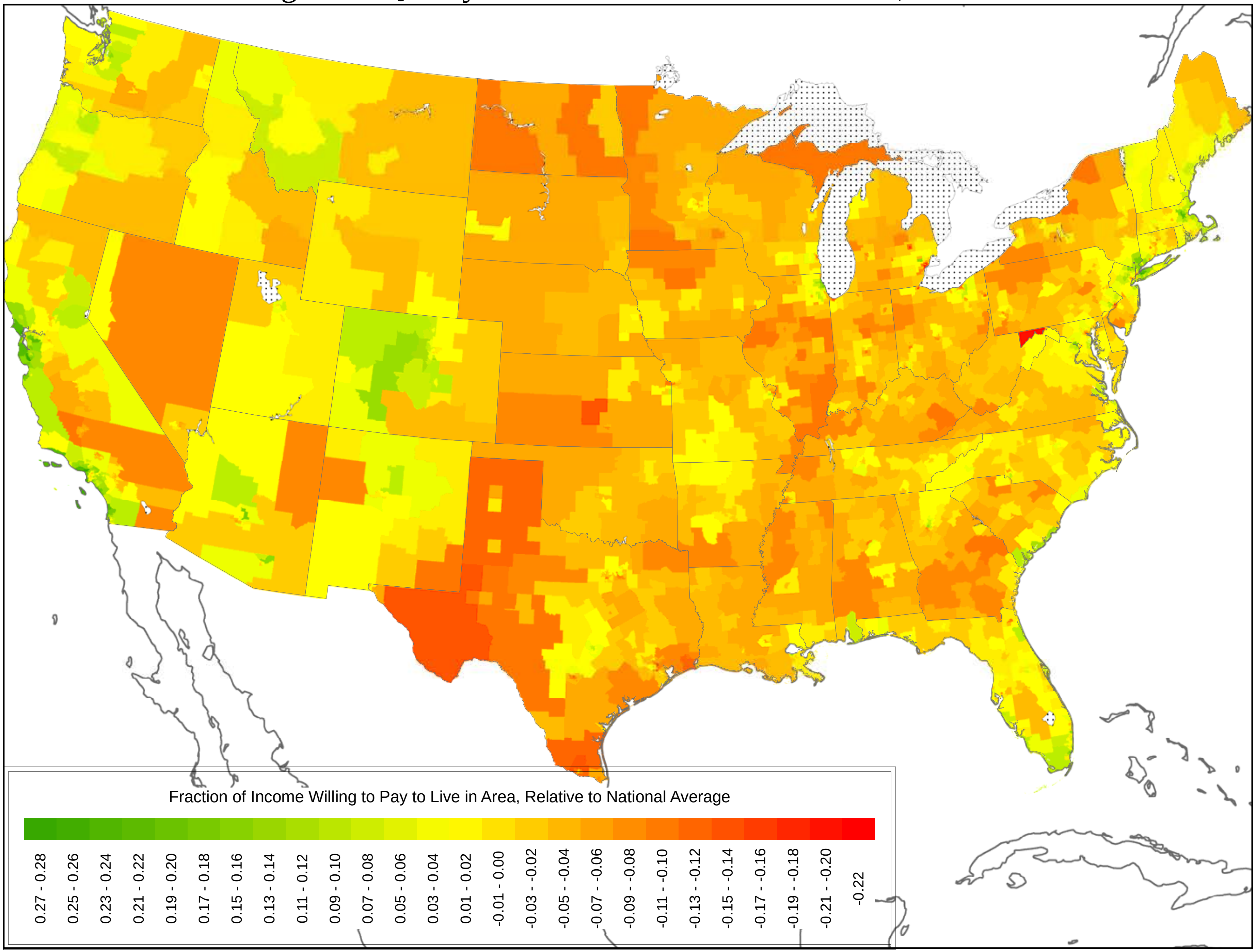


Figure 5A: Quality of Life in the San Francisco Bay Area, 2000

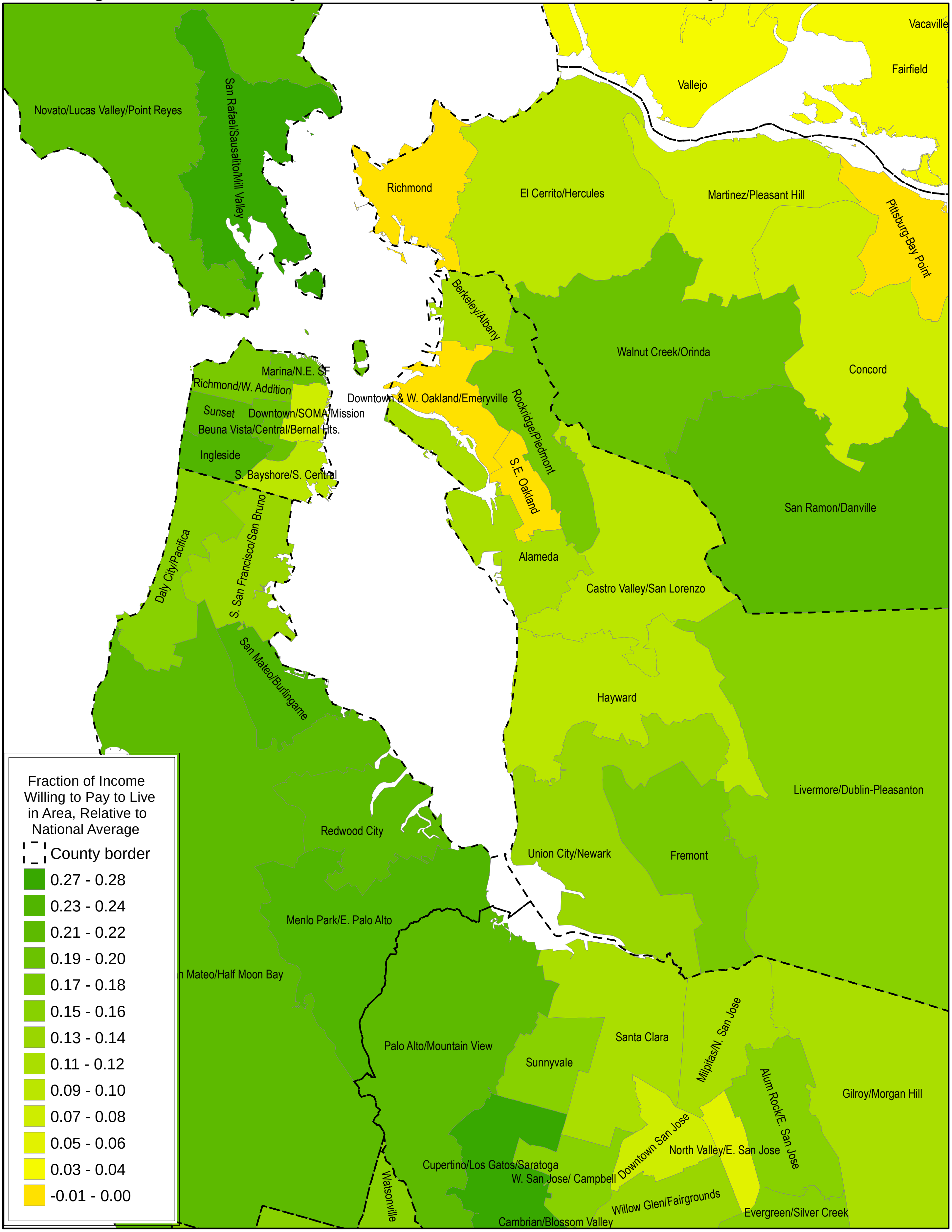


Figure 5B: Quality of Life in and around Manhattan, 2000

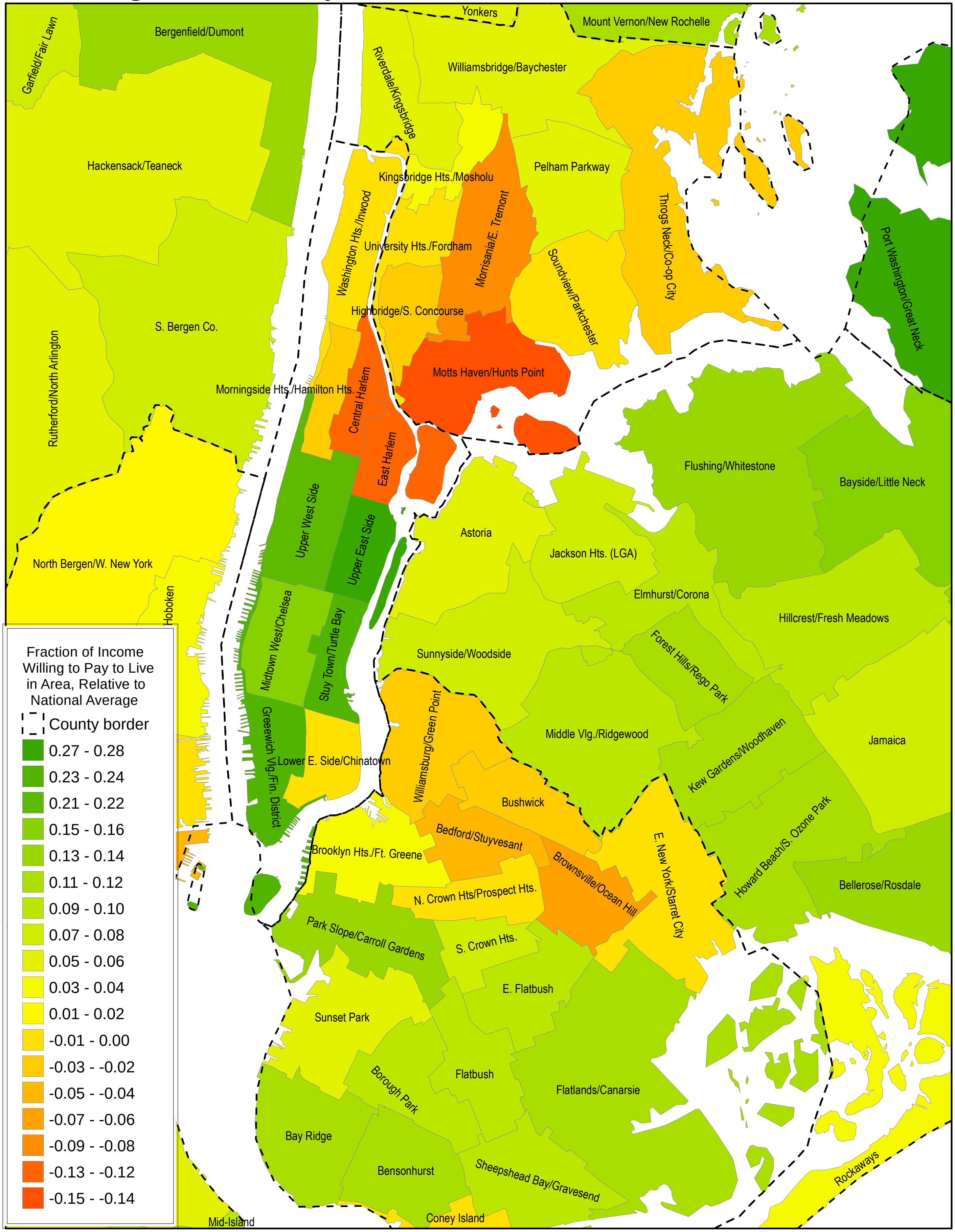


Figure 5C: Quality of Life in Detroit and Southeast Michigan, 2000

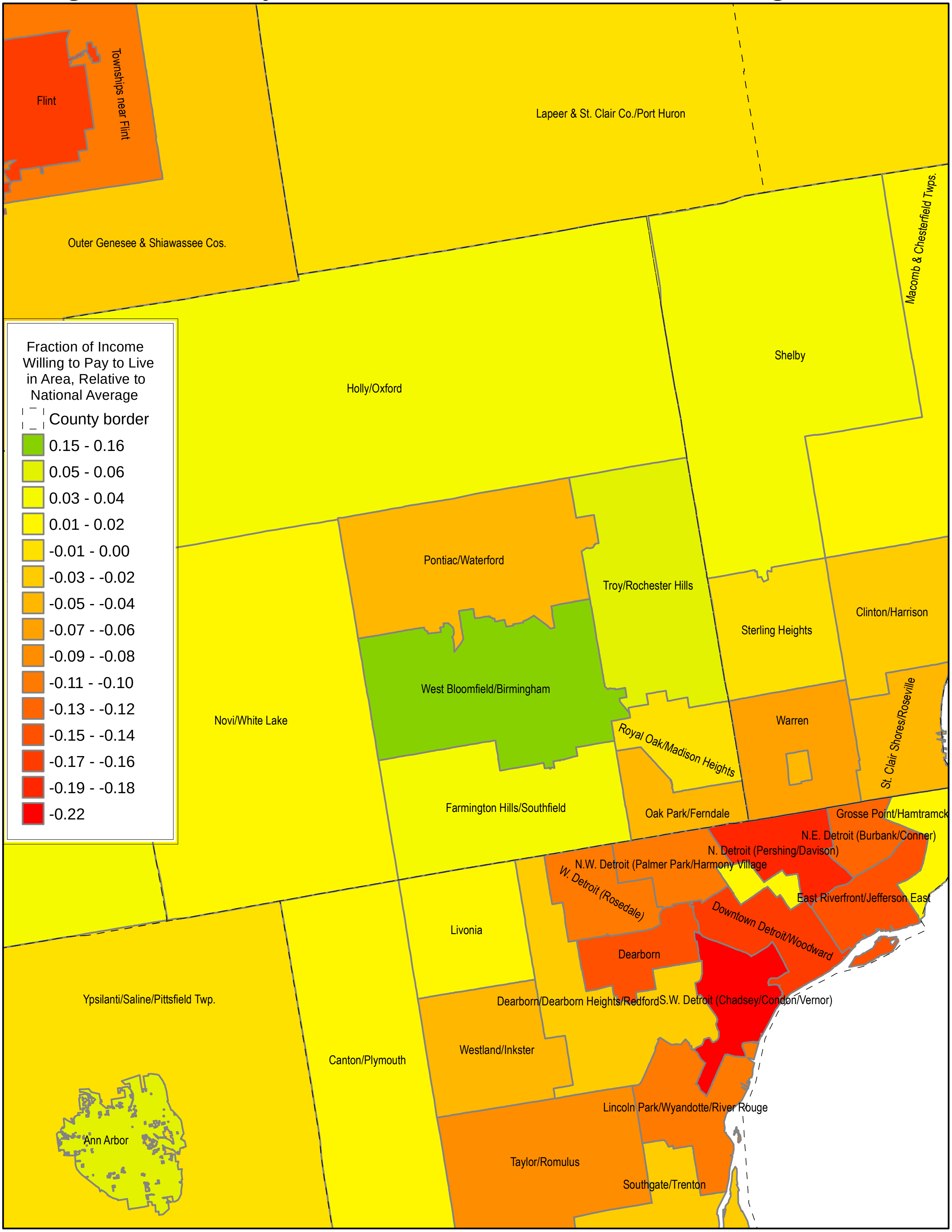


Figure 5D: Quality of Life in and around Atlanta, 2000