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

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**ABSTRACT**

In an equilibrium model of residential and workplace choice, we estimate local willingness-to-pay measures for 2071 areas covering the United States. These measures are based on how high residential housing and commuting costs are relative to workplace wages; they index quality of life when preferences are sufficiently homogeneous. 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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An online appendix is available at:
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# 1 Introduction

Households face many choices over where to live, both within and across metropolitan areas. These choices involve many trade-offs, as areas with better quality of life and labor markets are often more expensive and subject to longer commutes. Below, we consider how these trade-offs interact in an equilibrium model where they presumably offset each other. This allows us to construct a measure of local willingness-to-pay for amenities by residential location, based on how high housing and commuting costs are relative to the wages workers receive in their workplace. In essence, the measure uses observable values from local constraints to infer unobservable values from amenities. If tastes are sufficiently homogeneous, the willingness-to-pay measure provides a quality-of-life (QOL) index, summarizing the desirability of all local amenities combined, from culture to climate, and schools to safety. We provide a quality-of-life index that is unique in that it covers the entire United States at the finest level of geography for publicly-available micro-data.

To make an index that is sensible both within and across metro areas, we combine insights from two literatures of how local wages and housing costs, or "rents," are determined: one on local amenities, the second on commuting. In section 2, we motivate our work in the context of these two literatures. We synthesize relevant theories in section 3 to justify adding commuting to housing costs, to provide a fuller measure of the urban costs households pay for local opportunities. Our method stresses that wage differences are more accurately estimated from workers' place of work — rather than their place of residence — and provides a transparent way of estimating the combined value of local amenities.

Using U.S. Census data, we describe the components of the quality-of-life index — rent, wage, and commuting costs — in section 4. We use the Public Use Microdata Area, or "PUMA," level of geography to describe how these components vary 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 these measures is due to locations themselves, as opposed to the characteristics of workers or housing units. Among other findings, we relate that wage levels by location vary much more across metro areas than within. At the same time, household sorting according to observed skills is stronger within metros than across them. Rents by location vary far more within metro areas than wages do, and are not strongly related to observed housing quality. Controlling for local wages, rents fall weakly with commutes, which suggests that workers travel longer in the pursuit of amenities.

Our measure of quality of life, assembled and mapped in section 5, shows interesting and plausible heterogeneity across the United States. Many of the most amenable communities are along the Pacific Ocean, while many less amenable areas are often inland. Nevertheless, most major metro areas contain some highly coveted neighborhoods, even from a national perspective: there is as much variation in the quality-of-life index within metro areas as across them. In desirability, the best and worst neighborhoods in Manhattan more than span the averages of the best and worst states (Hawaii and West Virginia). We also map considerable variation in the metropolitan areas of Atlanta, Detroit, and San Francisco.

Lastly, in section 6, we find that a small number of amenities *predict* much of the quality-of-life index: households pay dearly to live in areas with mild temperatures, low crime, well-funded schools, and plentiful restaurants. Given the number of amenities we could examine, and heterogeneity in household tastes, we do not claim to produce reliable measures of the willingness-to-pay for particular amenities. Nonetheless, our estimates are often similar to those using more sophisticated techniques. Furthermore, estimates based on variation within metro areas are often similar to, or larger than, those based on variation across metro areas. This generally seems to support the index, but also suggests new directions for research. We briefly look at household sorting, and find a strong relationship between worker skills and neighborhood quality.

Since this paper is long, the reader is invited to skip to the sections they find most interesting.

## 2 Motivation and Related Literature

The two literatures on amenities and commuting are each very deep. When measuring the value of amenities within metro areas, most researchers since Oates (1969), focus on differences in rents.[1] Following Tiebout (1956), they ignore space by assuming that workers are mobile, have access to the same labor market, and that commutes can be ignored or controlled for. In addition, they assume preferences are homogeneous, in which case an overall quality-of-life index is given trivially by rental prices.

Rosen (1979) adapts this theory to different labor markets, arguing quality of life may be inferred from how high metro-level rents are relative to wage levels. It adapts the theory of compensating differences to both labor and housing markets by using individual amenities — chosen by the researcher — 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. The index is sensitive to the researcher's choice of relevant amenities.[2]

Albouy (2008) finds a strong relationship between housing and non-housing costs, and uses the former to infer the latter at the metro level, putting greater weight on housing-cost differences; meanwhile he puts less weight on wage differences to account for federal taxes. These adjustments make high-rent and high-wage areas, typically larger cities, appear more amenable. Albouy then uses a quality-of-life index constructed from indicator variables as the dependent variable in a second-stage regression to infer how much quality of life is predicted by observed amenities.

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 from metro-area indicators put in wage and rent regressions, instead of amenity variables. Implicitly, this index adds the value of observed and unobserved amenities together. Gabriel, Mattey, and Wascher (2003) add in a separate component for non-housing costs-of-living, albeit only at the state level due to data constraints. [3]

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

[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 neighborhood New York City. Streetadvisor.com relies on crowdsourced reviews written by users 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.

Our application goes beyond existing analyses on quality of life by accounting for commuting and place of work. Furthermore, it is the first, to our knowledge, to use the finest level of geography in publicly-available Census microdata, 2071 PUMAs. Thus, we can often examine differences in quality of life within counties.[4]

By involving commuting, we refer to the core urban literature on intra-urban price gradients. In a monocentric city model, Alonso (1964), Mills (1967), and Muth (1969) relate how lower rents should compensate households for higher commuting costs, producing rent gradients that fall with distance to a central business district. Hoehn, Berger, and Blomquist (1987) consider how a *city-wide* amenity may affect wages and prices, and conclude "the amenity valuation results of Roback's pure inter-regional case carry over." Muth (1969), White (1976) and Straszheim (1984) develop the theory of how wage levels should vary within a metro area. Wages typically fall away from urban centers and sub-centers as workers accept lower wages for shorter commutes.[5]

Empirical work on wage gradients (Eberts 1981, Madden 1985, Zax 1991, McMillen and Singell 1992) generally supports the hypothesis that wages fall away from urban centers. Evidence on rent gradients is more mixed (e.g. Dubin and Sung 1987), at least over short distances. A stark example is metro Detroit, where central-city land is often sold at lower prices and is less developed than suburban land. Much central land is abandoned or used for agriculture, land uses typically seen on the urban fringe. This mixture of evidence suggests that local amenities may be confounding predicted gradients. Gabriel and Rosenthal (1996) provide a useful theory for such

[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, aggregating from the public-use microdata areas PUMAs we use here. They incorporate many of the features new in Albouy (2008) regarding taxes and non-housing costs, albeit differently. They use wages by place of residence and deal with commuting by controlling for distance to the nearest urban center. They also correct for selection from inter-state migration using techniques adapted from Dahl (2002). While they find the Dahl correction important, we find it (see Appendix Table A2) 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 and use the projected value to determine relative quality of life. Since many amenities and 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]Turnbull (1992) examines the role of leisure in a related model and concludes that it makes little difference for examining wage gradients. "the introduction of leisure choice into the local employment location model does not alter either the form of the location equilibrium location condition or the immediate implication for the wage rate-distance relationship." This occurs since households put the same value of work and leisure on the margin.

an application, but use it to address the spatial mismatch of employment for minorities.[6]

In practice, estimates of local wage and rent levels may be biased by unobserved differences in worker skills or housing quality. Fu and Ross (2013) find that the positive effect of employment density on wages is unaffected by detailed controls for place of residence, but is rendered insignificant when commuting is controlled for. This finding supports theories of wage gradients and provides evidence that workers' unobserved earnings abilities (or "skills") are uncorrelated with where they work, even if they are related to their place of residence. 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.

# 3 A Model of Residential Choice with Commuting

## 3.1 Household Preferences and Constraints

We incorporate commuting into the canonical model of Rosen (1979) and Roback (1982), expanded by Albouy (2008) to accommodate federal taxes, non-housing costs, and non-labor income. Households are homogeneous, mobile, and have full information about every community. They consume a tradeable 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, $\mathbf{Z}$. Amenities are aggregated into a single quality-of-life index, $Q = \tilde{Q}(\mathbf{Z})$. Household preferences are then 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 $Q$, meaning that preferences for consumption goods and amenities are weakly separable.

Households choose their place of residence, $j$, which differ in local prices, $p^j$, and amenities, $Q^j$. They also choose their place of work, $k$, which differ in the wage, $w^k$, where they choose their hours, $h$. Commuting between home and work takes time $f^{jk}$, and is assumed to have a propor-

[6] We believe work on racial segregation to be extremely interesting and important for many areas, including that related to the spatial-mismatch hypothesis. For now, we defer questions on this 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 they impact wages.

tional 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 fully-diversified share of land and capital in the economy. They pay federal taxes $\tau(w^j h + I)$, which are rebated lump-sum back in $I$. State taxes and tax benefits to owner-occupied housing are modeled in Appendix C.[7] 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 $u$:

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

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 $\partial e/\partial w,\ \partial e/\partial Q \leq 0$.

## 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 homogenous, all observed combinations $(j, k)$ must provide the same level of utility, $u$. This equilibrium can be characterized neatly with the expenditure function:

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

[7]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.

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, $df^j$ are changes in commuting time due to varying residences. This expression generalizes the housing-cost, or rent, gradient: higher rents may be associated with lower commute times or higher quality of life. Households may commute longer to consume better amenities, and rent gradients may rise with distance to work if quality of life improves.

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. Yet, the purpose here is not to test whether these gradients hold. Instead, we combine (2) and (3) to infer local willingness-to-pay measure for changes in quality of life, $dQ^j$. This yields the expression $-(\partial e/\partial)dQ^j = (\partial e/\partial p)dp^j + (\partial e/\partial w)dw^k + (\partial e/\partial f)df^{jk}$ 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 $Q$.[8] 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, $(1-\tau')\bar{h} \cdot dw^k$.[9] Alternatively, high wages compensate workers for high urban costs or low amenities.

## 3.3 Applying and Parameterizing the Model

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

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

where $s_y = \bar{p}\bar{y}/\bar{m}$ is the expenditure share for home goods, $s_w \equiv \bar{w}\bar{h}/\bar{m}$ is the income share from labor, $s_c \equiv c\bar{f}/\bar{m}$ is share of income spent on commuting, and $\bar{f}/\bar{h}$ is the 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 $s_w = 0.75$, $s_y =$

[8] Since Q does not have natural units, neither $p_Q$ nor $dQ^j$ alone have operational meaning, although their product, $p_Q dQ^j$, does as the marginal willingness-to-pay to enjoy the amenities in location $j$.

[9] 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, have (orthogonal and mean zero) preferences of location, or receive idiosyncratic wage offers from different locations, each with mean $w^k$, 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).

$0.33$, and $\tau' = 0.35$. This allows 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.[10]

For the commuting parameters, we use information from the Survey of Income and Program Participation (SIPP) and National Highway Summary of Travel Trends. First, we take into account that monetary costs depend on the mode of commute. We use the median percent of income spent on commuting by mode from the SIPP to account for how median monetary costs depend on the 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 found that the average worker in 2000 worked 1822 hours (U.S. Census) and spent 184 hours commuting. The fraction of time spent commuting is therefore set at $\bar{f}/\bar{h} = 0.10$.[11]

The greatest uncertainty involves the parameter $\alpha$: marginal commuting time is valued as work time if it equals zero, and 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. This assessment is based on more recent evidence from Small et al. (2005) from stated and revealed preference, and Fu and Ross (2013) from wage gradients, that commuting is not preferred to working. It is reinforced by subjective well-being data from Kahneman and Krueger (2006) which shows that subjective affect while commuting as is low or lower than while working. Alternate values of $\alpha$, which could be negative or positive, may be accounted for easily.

Overall, the quality-of-life measure proposed in (5) extends existing theories in a straightforward manner. It makes transparent how quality-of-life measures depend on alternate parametrizations or estimates from the data. We turn attention to these estimates now.

[10] See Appendix C.2 for full details of state tax calibration.

[11] Annual commuting time is the product of 418 commuting trips, averaging 26.4 minutes each way. The cost of commuting time is assumed equal by mode, although this assumption is worth further research.

# 4 Wage, Rent, and Commuting-Cost Estimates

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).[12]

## 4.1 Units of Geography

The public-use files identify households' location of residence down to 2071 Public Use Microdata Areas, with an average population of 135,887 each. The Census Bureau does not provide names for the PUMAs, although in many cases 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 another refers to areas in Washtenaw County outside the city. In the borough of Manhattan, also known as New York County, NY, ten areas are identified which correspond to sub-boroughs, such as the Upper East Side and Central Harlem. 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.

Metro areas are formed from counties. For ease, we use the 1999 definitions from the Office of Management and Budget (1999). These definitions include 276 Metropolitan Statistical Areas (MSAs) — such as that for Athens, GA, which coincides with the three counties listed above. We also group non-metro areas for each state as an MSA unit. 19 MSAs are categorized as Consolidated MSAs (CMSAs) which are in turn made up of 55 Primary MSAs (PMSAs). Thus, from

[12] We acknowledge that the quality-of-life estimates are slightly out of date, and that some changes have already occurred in areas such as Brooklyn in New York, or the Mission in San Francisco. Nevertheless, the 2000 Census offers the last large (5 percent) snapshot of the U.S.: the American Community Survey only offers 1 percent samples each year. Furthermore, we are worried about biases that might be introduced by using housing prices in the wake of the boom and bust cycle, meticulously detailed in Ferreira and Gyourko (2011), which may not be driven by market fundamentals. Furthermore, recent evidence in Lee and Lin (2013) highlights remarkable persistence in the desirability of most neighborhoods, especially in areas with natural amenities.

2071 PUMAs we may assemble the data into 3081 counties or county-equivalents, 373 PMSAs or PMSA-equivalents (counting straight MSAs and non-metro areas of states), and 327 MSAs or MSA-equivalents (putting the 55 PMSAs into 19 CMSAs).[13]

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*.[14] We also classified 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 County, NY (Manhattan), and San Francisco County and City, 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 be consistent with previous studies, we impute rents for owned housing by multiplying housing values by a rate of 7.85 percent (Peiser and Smith 1985), to which we add utility costs, to make them comparable to gross rents for rental units. We regress rents on place-of-residence indicators, $\mu_p^j$, and controls for housing composition, denoted $X_{pi}^j$ – i.e., size, rooms, acreage, commercial use, kitchen and

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

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

plumbing facilities, type and age of building, and residents per room – all of which are fully interacted with renter status.[15] The resulting regression equation is

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

where estimates of $\mu_p^j$ 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 call "housing quality," although since it involves measures like the number of rooms, it also refers to quantities of housing.

Another issue is that the Census does not provide information about rent control. This is important in a few prominent cities. Using Pollakowski (2003), we impute what rents would be without control, causing them to be slightly higher in core Manhattan and San Francisco.[16]

Identifying the rent differentials requires that mean differences in unobserved housing quality across areas are orthogonal to the location index. This condition may not hold. Two-bedroom apartments built in the 1960s in the Chicago suburbs may be more spacious or better-maintained than ones built contemporaneously in central Seattle. An overstated rent differential will bias quality-of-life estimates upwards; one must bear in mind that quality of life may also capture differences in unobserved housing quality. Our fears of this bias are somewhat mitigated by the fact that the correlation between locational rent and observed quality measures is zero across PUMAs, as shown in Appendix Figure A3.[17] The Appendix also contains a map of the rent index (Figure

[15]We combine rent and imputed-rent measures to avoid potential problems created by local differences in homeownership (see Table A1). 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. Because of our controls for tenure status, the rate we use makes no difference except for how utility costs are integrated, which is very minor.

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

[17]For instance, we find the compositional component very high in parts of suburban Atlanta (e.g. Alpharetta, Snellville), although the location c is quite average. Meanwhile, the compositional component is quite low where the locational rent is high, such as 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

A1), a summary of related housing measures (Table A2), and detail the variables.

In Table 1, we see rents are 2 percent higher in the suburbs than in central cities, despite longer commutes. This seems contrary to standard rent-gradient predictions, but rents do eventually taper off. 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.

In column 3, we see that housing quality in central cities are 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 primarily because units in denser, central areas are older and have fewer rooms.

Panel C provides evidence that differences in housing costs across areas due to observable quality are considerable, but that differences due to location are much greater. At the PUMA level, rents vary more across metro areas, than within them. The opposite is true of differences in composition, which are relatively small across metro areas.

## 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, $\mu_w^k$, 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 $\mu_w^k$, 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. In the Appendix, we map the wage index (Figure A2), summarize related worker measures (Table A3), and detail the variables.

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.

Identifying wage differentials requires that workers do not sort across workplaces according to their unobserved skills. As mentioned earlier, Fu and Ross (2013) find that wage premia from agglomeration economies are unaffected by such sorting. They use place of work identified at the PUMA level with confidential data; place of work in the public-use files is only available of at the coarser Place of Work Public Use Microdata Area (PWPUMA) level. These number 1240, and are made up of the 2071 standard PUMAs. Fu and Ross (2013) do reach the same conclusions using PWPUMAs, but the coarseness of the geography eliminates some wage differences mechanically. While less than ideal, we believe this is preferable to using wages by place of residence with finer geography.[18]

To justify this preference, we examine the consequences of using wages by residence. In Table 2, we see wages by residence vary remarkably in Manhattan: they are 58 percent (46 log points) above average in the Upper West Side and only 5 percent above average in Washington Heights. This wage difference is hard to interpret causally because the two are areas are so close: they are separated by a 14-minute subway ride, with a $1.50 fare in 2000, or a 15-minute taxi ride, costing $13 including tip (in current 2000 dollars, the average hourly earnings were $14 and the minimum wage was $5.15). Within San Francisco, we see Downtown offers wages 19 percent above average, while Northeast San Francisco, which is primarily residential, offers wages 47 percent above average. These neighborhoods are adjacent, with most areas connected by a short walk, drive, or bus ride. Furthermore, morning traffic is much thicker going downtown. If differences in wage levels by residence represent true opportunities, then commuting behavior is often in the wrong direction, and workers could gain tremendously by changing their place of work.

Figure 1 graphs wage estimates by place of work against those by residence. We see that the the former vary less than the latter. By place of residence, wages in the Long Island suburbs are

[18] Appendix D has more details on PWPUMAs. In Table A2, 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.

often as high or higher than in Midtown and Downtown Manhattan. By place of work (the two have different PWPUMAs) wages in Long Island are substantially lower than in Manhattan. Nevertheless, on average, workplace wages in the suburbs are as high as in central cities. Residential wage measures indicate wage opportunities are on average lower in central cities, more strongly opposing standard wage-gradient predictions.

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, although wage gradients are not negligible. On the other hand, wages due to observed skills vary much more within metro areas than across them. This fact supports the hypotheses that residential sorting is more of a within-metro phenomenon, and that wage differences across metros are due more to the productivity of local firms.

We may interpret the differences between residence and workplace wage measures as reflecting unobserved skills. In figure 1, 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, strengthening the hypothesis that within-metro sorting is stronger.

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 North Beach. Unmeasured differences in unobserved skills may bias quality-of-life estimates upwards if an area with low-skilled workers is confused for an area where wage opportunities are weak.

## 4.4 Commuting Costs

We estimate commuting-cost from 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, $\mu_f^j$, 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. Overall, the predictive power of the regression is rather low, and so we forgo discussion of time predicted by observable characteristics.[19]

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. We use modes only to determine monetary costs. Using a linear probability model, we calculate demographically-adjusted probabilities of using each mode of transportation, $\rho_l^j$, for modes $l$ – own car, carpool, public transportation, and other methods, including 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 typically minor, since most people drive.[20] The Appendix details these methods and summarizes the component measures in Table A4.

Column 7 in Tables 1 and 2 report differences in the full index of commuting costs $\hat{c}^{jk}$, the last term of (5). It depends primarily on commuting time in column 8. These costs are lower in central cities and non-metro areas than in the suburbs, although the variation is small economically. Within metros, downtown residents have the lowest observed costs. Commuting costs are lowest in low-density areas, and at the PUMA level these costs are slightly less within metropolitan areas as across them. The map in Figure 2, helps to illustrate these facts. In some large metros, like Atlanta, Dallas, and Houston, we see commuting costs have an annulus or "donut" pattern. In

[19]The R-squared is 0.08 using the square root. Using powers of 0.25 and 1 (linear) caused even worse fits.

[20]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.

other metros, the patterns are more asymmetric: in Detroit they are rise going north; in Boston, 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. The cost measures are provided in Appendix Table A6, and are contained in Appendix A and Table A3.

Within metro areas, it appears that commuting costs obey the patterns predicted by the standard urban model even better than rents and wages. Figure 3 plots commuting costs relative to housing costs, controlling for local wage levels.[21] 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. Unless workers like commuting more than working, this suggests that residents are commuting longer for better amenities.

## 4.5 Other household characteristics

A concern about the validity of the quality-of-life estimates is that households may have different tastes for amenities. This is a valid point. The Pew Research Center (2009) compares how individuals of different ages, gender, income, and education state their preference metro areas. They find some differences. 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.

Keeping this in mind, in Appendix Tables A2 through A5 we examine variation in observable characteristics to look for evidence of sorting. Evidence along many characteristics is rather weak. Table A4 summarizes how some of these demographic characteristics vary. The proportion of children under 18 is about 28 percent in central cities, suburbs, and non-metro areas; this number hardly varies by density either. The standard deviation is only 4 percentage points across PUMAs.

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

Household size also varies little. 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. There is a small difference in the marriage rate: 37 percent in the central city versus 45 percent in the suburbs.

Some differences are notable. Central-city residents are twice as likely to be black, but they are only 20 percent of the central-city population. Immigrants are also more concentrated in denser and more urban areas. Lastly, home ownership rates are much higher in suburban and lower-density areas, although this may have much to do with the single-family buildings residents there occupy.

# 5 Quality of Life across the United States

We combine the rent, wage, and commuting differentials to estimate average local quality of life — or, more loosely, local willingness to pay — from equation (5).[22] The comprehensive geographic information provided by Census 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. Quality-of-life differentials for these four MSAs, and for Honolulu, are presented in Table 3. In places we find interesting, we break our estimate up by according to four geography levels: 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. Table A6 lists ranks and lists 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, accessibility to Honolulu, and Diamond Head volcano. To live here, households sacrifice the equivalent of 29 log points of real after-tax income (25 percent) relative to the national average. This PUMA is inside the Honolulu

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

MSA, which was already found to be the highest quality-of-life MSA in Albouy (2008).

The highest ranked county is Marin, 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. 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 PMSAs, including Santa Cruz (#3), San Jose (#4) and Oakland (#11), the Combined MSA is ranked second, just behind Honolulu. [23]

New York City, with its high population density and world renown, is an especially interesting case. 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. Yet, it may still come as a shock that neighborhoods a mile apart could represent almost the full range of quality of life from a national perspective. After all, these areas share the same geography, climate, and municipality. 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 worst quality of life is found in southwest Detroit City, in the area containing the neighborhoods of Chadsey, Condon, and Vernor (see Figure 5C). As far as we can measure, households are compensated with 25 percent (22 log points) of real income to live there (seen in Table A6). Although the Detroit MSA does not have particularly valuable amenities on average, some of its suburbs have attractive amenities. The PUMA containing West Bloomfield and Birmingham

[23] 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.

ranked 73 among PUMAs, in the top 5% of PUMA rankings. Detroit has two satellite PMSAs, Flint and Ann Arbor, with contrasting central cities. Although both have higher than average wage levels and commute times, the much higher rents in Ann Arbor signal its attractiveness.

Differences in the Atlanta area are not quite as stark. The greatest range is within the city of Atlanta, between adjacent PUMAs: one containing Buckhead, the other, Center Hill and West Lake. The PUMA containing Midtown and Downtown is in the middle. Fulton county, containing most of Atlanta, is surpassed in average quality of life by DeKalb (with Decatur) to the east, and Cobb (with Marietta) to the west.

Due to the idiosyncrasies of each metro areas, it is difficult to infer particular patterns, except that there are considerable differences in quality of life within metro areas. The results in column 9 of Table 1 make more sense of the national patterns. On average, households seem to prefer suburban areas to central cities, as they pay 2 percent more in rents, and endure commutes 10 percent longer to get the same wages. However, Americans would typically sacrifice 4 percent of their income be in a a central city than outside of a metro area altogether:

Even though central cities tend to be denser than the suburbs, denser areas are generally more amenable. About twenty percent of suburbs have a density of over 5,000 per square mile high density, for instance Laguna Beach. High-density suburbs offer a quality of life of 5 percent above average. Many parts of central cities, have densities below 5,000, such as downtown Kansas City. Medium-density central cities offer a quality of life 3 percent below average. This does not prove that density is itself desirable: populations are attracted to quality of life. Density also depends heavily on local housing supply.

The results in Panel C formalize the finding that there appears to be about as much variation within metro areas as across them. At each level, the standard deviation in values is almost 5 percent of gross income. While technically, the variation within metro areas is slightly lower, it is understated, since PUMAs obscure variation at lower levels of geography. Thus, there is likely to be even more variation within metros than across metros. This is remarkable: as will see below, many amenities vary far less within metro areas than across them.

To highlight why accounting for commuting is important, column 10 presents estimates of quality of life if we ignore commuting costs and estimate wages by place of residence. If we ignore commuting, suburbs look less desirable than central cities, and larger metro areas look less desirable, especially relative to non-metro areas. Without commuting, San Francisco MSA would fall from number 2 to 4, behind the Santa Barbara and Salinas (Monterey Co.) MSAs, which offer lower wages and shorter commutes.

On both ends of the commute, workers put up with higher commuting costs to get the wage and amenities that they want. While both wages and housing costs vary less within MSAs than they do across MSAs, these examples match the general trend that within an MSA, wages vary less than rents do. This reinforces the notion that the effective size of a labor markets is larger than that of a residential neighborhoods. When households move to a city, they typically have more options in the neighborhood conditions of where they live than where they work.

# 6 Predictors of Quality of Life

## 6.1 Quality of Life and Individual Amenities

In this section we consider how well the quality-of-life index is predicted by measures of specific local amenities, bearing in mind that these relationships may not be causal. If amenities are exogenous and households have the same preferences, then we can use a basic hedonic equation to estimate the average marginal willingness-to-pay for specific amenities. We follow Albouy (2008) by running the following regression:

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

where $\pi_k = -(\partial E/\partial Q)\left(\partial\tilde{Q}/\partial Z_k\right)/\bar{m}$ measures the fraction of gross income a household is willing to pay for one more unit of amenity $k$. Multiplying this coefficient by average gross household income ($68,000 in 2000) produces a dollar value. The residual $\varepsilon^{Qj}$ results from measurement error, unobserved amenities, mis-specification, and unobserved housing quality and worker skills.

Inferring specific amenity values using this standard hedonic technique is subject to well-known caveats.[24] In fact, one of the advantages of using an overall revealed-preference estimate of quality of life, is that we do not need to specify the amenities that determine it. The index may capture important unobserved (to the econometrician) amenities, such as smells, the beauty of local gardens, the friendliness of other residents, and the exterior charm of local architecture. Nevertheless, it is somewhat reassuring if the quality-of-life index has significant partial correlations of the "correct" sign of ostensibly desirable amenities, even if the regression coefficient is contaminated with various biases. "Incorrect" signs on important amenity variables would almost certainly sow doubt. [25]

Thus, the exercise here is to examine how well the quality-of-life index is *predicted* by seemingly important amenity measures using the standard apparatus of a hedonic regression. More originally, we examine whether estimates within metro areas are similar to those identified across all areas. We do this by adding MSA indicators, or "fixed effects," to the regression. This reduces the identifying variation, but may help to validate some of the estimates, particulalry if endogenous effects are omitted variable biases are different within metro areas relative to across them. We may also compare our estimates with others in the literature, which use more sophisticated methods, typically for one metro at a time.

Our amenity variables are described in Appendix B, and summarized in Table A6. It is worth

[24] 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. There may also be important non-linearities in the hedonic equation.

[25] Oftentimes there are few alternatives to using plain spatial variation. Amenity variation over time that is plausibly orthogonal to other unobserved factors is only available in some cases — see Davis (2004) for health and Chay and Greenstone (2005) for air quality. Cellini, Ferreira and Rothstein (2010) use a particularly innovative method using votes on bond issues to value school facility investments. Crime has 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). Furthermore, over time, residents may re-sort across neighborhoods, causing issues with the estimates — see Kuminoff and Pope (2013) and Banzhaf (2013). Other studies that use spatial discontinuities, such as district borders — see Black (1999)— are subject to sorting effects (Bayer, Ferreira, and McMillen 2007). Many amenities, like climate or geography, hardly change at all, 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. They find some evidence that people in colder climates are more averse to heat.

noting here that three climate variables — measuring the 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. Murder rates as well as bars and restaurants vary more within metros than across, and are concentrated in central and denser areas. Public school revenues exhibit less variation within metros, and appears to be highest in the suburbs and lowest in non-metro areas.

Table 4 reports the estimates from the amenity regressions. The eight variables explain 40 percent of the variation in quality of life over all PUMAs. The results that households value mild winters, mild summers, sloped land, sunshine, and coastal proximity are already discernible from cross-metro estimates in Albouy (2008) and are explored in greater depth in Albouy et al. (2013). The main observation is that the coefficients for the temperature and slope variables are still relatively precise within metros and slightly larger. The sunshine estimate is understandably imprecise, partly because we have fewer weather stations measuring it than metro areas. The coastal estimate however, is almost as precise but 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).

We proxy for safety using the minus murder rate. Metro-level regressions do not provide evidence that households are willing to pay to avoid crime, measured through the murder rate (see Albouy 2008). Although we were only able to obtain crime rates 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 a quality-of-life reduction of $1,000 to $1,600 per household, depending on the specification. This number is certainly influenced by other correlated amenities.[26] Nevertheless, it is smaller than crime valuations in Bishop and Murphy (2011), based on geographically finer data for the SF Bay Area.

The estimates also reveal a strong association with school funding even if those require higher

[26]It is worth noting that crime victims may not be local residents of the crime.

local taxes, which 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 may just result from well-funded areas being nicer in a number of unobserved ways. If we interpret this number causally it might indicate that schools are underfunded, especially if, on the margin, households fund schools out of local taxes (see Brueckner 1982). These estimates have the same order of magnitude as Cellini, Ferreira, and Rothstein's (2010) estimate of the value of school facilities and Black (1999), Bayer, Ferreira and McMillan (2007), and Caetano (2010), estimates the willingness to pay for schools with higher test scores. The estimates of school spending appears to be roughly the same within as across metro areas.

Lastly, as a measure of local entertainment opportunities, we use the number of local bars and restaurants. The effect is statistically significant. Economically, each bar or restaurant increases the willingness-to-pay of 1,000 locals by $170. In total, this is $170,000 total per establishment, roughly a third of the average revenue of a restaurant. While this large number is not implausible, it is likely influenced by other retail and entertainment establishments, neighborhood atmosphere (net of disruption), and the characteristics of local residents.

## 6.2 Household Heterogeneity and Sorting

Thus far, our analysis has said little about household heterogeneity or sorting across neighborhoods. This is a complex topic with a quickly developing literature. As mentioned in section 4.5, sorting along many observable dimensions — age, education, employment status, household size — seems often modest between city and suburb. Nevertheless, there are many other important dimensions of sorting to be considered; too many, for the remaining analysis.

To provide a simple test of sorting, we use a single index of household heterogeneity, namely wage income predicted by worker composition, or "skill," as we called it. The correlation between this single-index of skill with the single index of quality of life is 0.44. It appears that, on average, households with greater purchasing power consume more amenities. This correlation is consistent with a low substitutability between amenities and consumption goods (e.g. Epple and Seig 1999), or that amenities are more income elastic than housing (e.g. Black et al. 2009). We leave further analysis for future work.

Perhaps the greatest issue not modeled here is how households sort according to their tastes for particular goods or amenities. For example, the strong willingness-to-pay for suburbs with well-funded schools could result from parents with children having the strongest demand for housing. Further research is certainly warranted in measuring the willingness to pay for different amenities across households, according to both observed and unobserved traits. Nonetheless, the importance of preference heterogeneity should not be overstated: we imagine that if their private consumption were held constant, most Americans would prefer to live by beaches in Hawaii than by abandoned houses of Detroit.

# 7 Conclusion

Given how many amenities hardly vary at all within metro areas, it is somewhat surprising to see that the overall willingness-to-pay to live in different neighborhoods vary as much within metros as across them. The variety in quality of life within metros seems to exceed that of wages, providing support for the hypotheses that that employment decisions have a stronger component across metros, while residential decisions are more important within them.

Our adjustments for commuting seem to improve estimates of quality of life, particularly at the sub-metropolitan level. They help us distinguish low-wage areas with good amenities from those where workers have low skills. Second, they help us recognize that suburbs and denser areas, with longer commutes, are somewhat more desirable than simpler measures imply.

While we cannot make strong claims about how much households are willing to pay for specific amenities, we did find reassuring evidence that our quality-of-life measure is strongly predicted by a parsimonious list of plausible amenity measures including schools, safety, and slope of the land. Estimates based on variation within metro areas are typically agree or are slightly larger than estimates using across-metro variation. Furthermore, workers with greater earnings tend to locate in more desirable locations.

This analysis suggests important directions for future research. Across metro areas, it appears that household sorting is less of an issue and that natural amenities, such as climate and geography, play a bigger role in determining an area's desirability. Within metro areas, local amenities (such as safety) are more artificial, and depend more on local populations to produce and fund them. It would be interesting to model whether the larger coefficients on the amenity variables within metro areas are due to stronger feedback effects. Namely, desirable (or undesirable) amenities may attract households that produce other desirable (undesirable) amenities. This effect could be larger within metro areas because transportation costs are far lower, allowing for greater household sorting. The often extreme differences in quality of life between neighboring areas suggests that some kind of self-reinforcing mechanism may be at play. These topics, related to the production of amenities, should be of great concern to local policy makers, since they have greater influence on the more localized artificial amenities that are particularly variable within metro areas.

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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 (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) |
| *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: 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 |

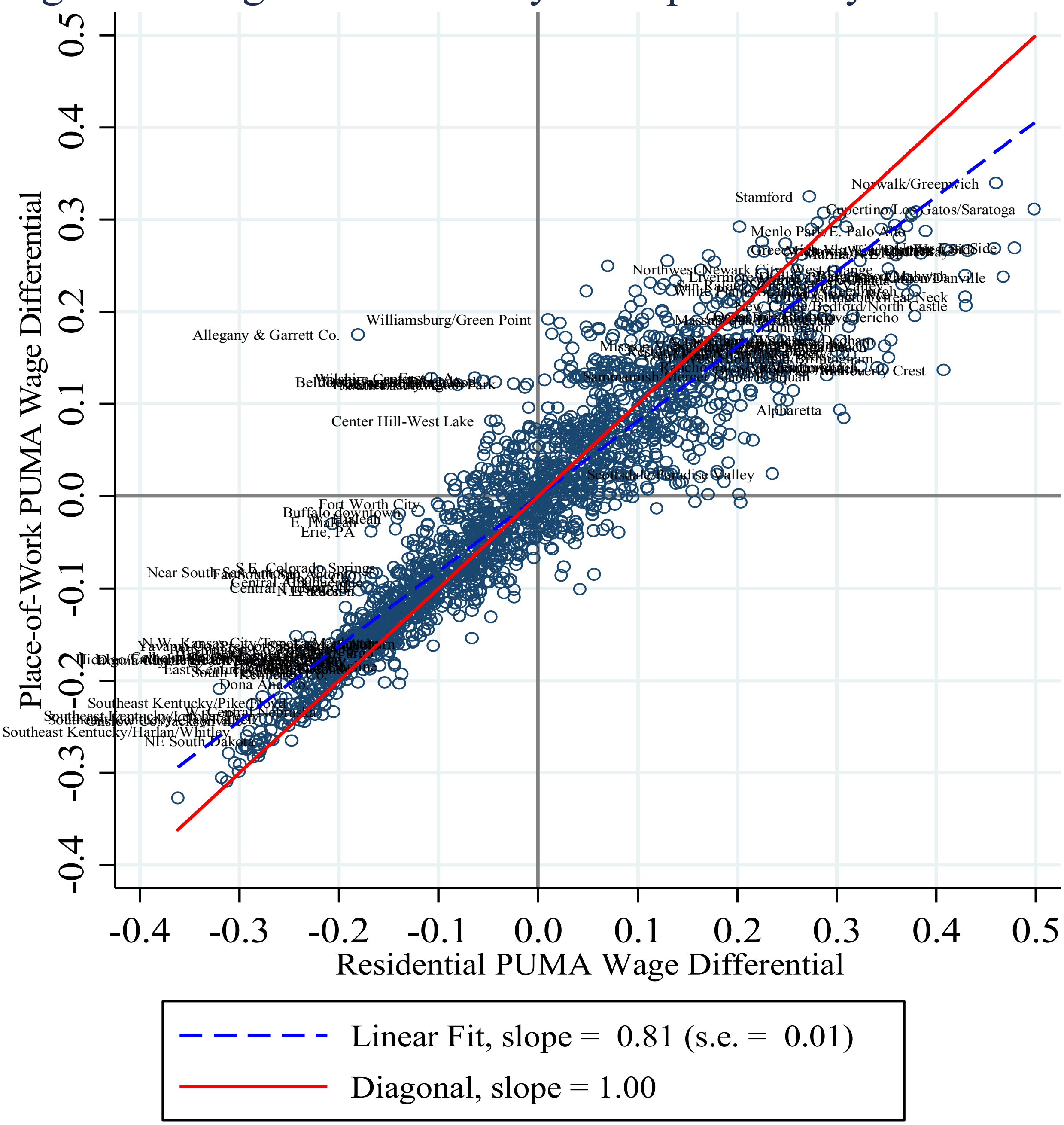
Units of geography are MSA, PMSA, County, and PUMA. MSAs that contain several PMSAs, are also called "CMSAs". The PMSA ranking also includes MSAs that do not contain PMSAs. Counties may be larger, equal to, or smaller than PUMAs. For example, one PUMA constains St. Clair & Lapeer counties, and so they 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 4: HEDONIC ESTIMATES OF THE VALUE OF INDIVIDUAL AMENITIES

| 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 |

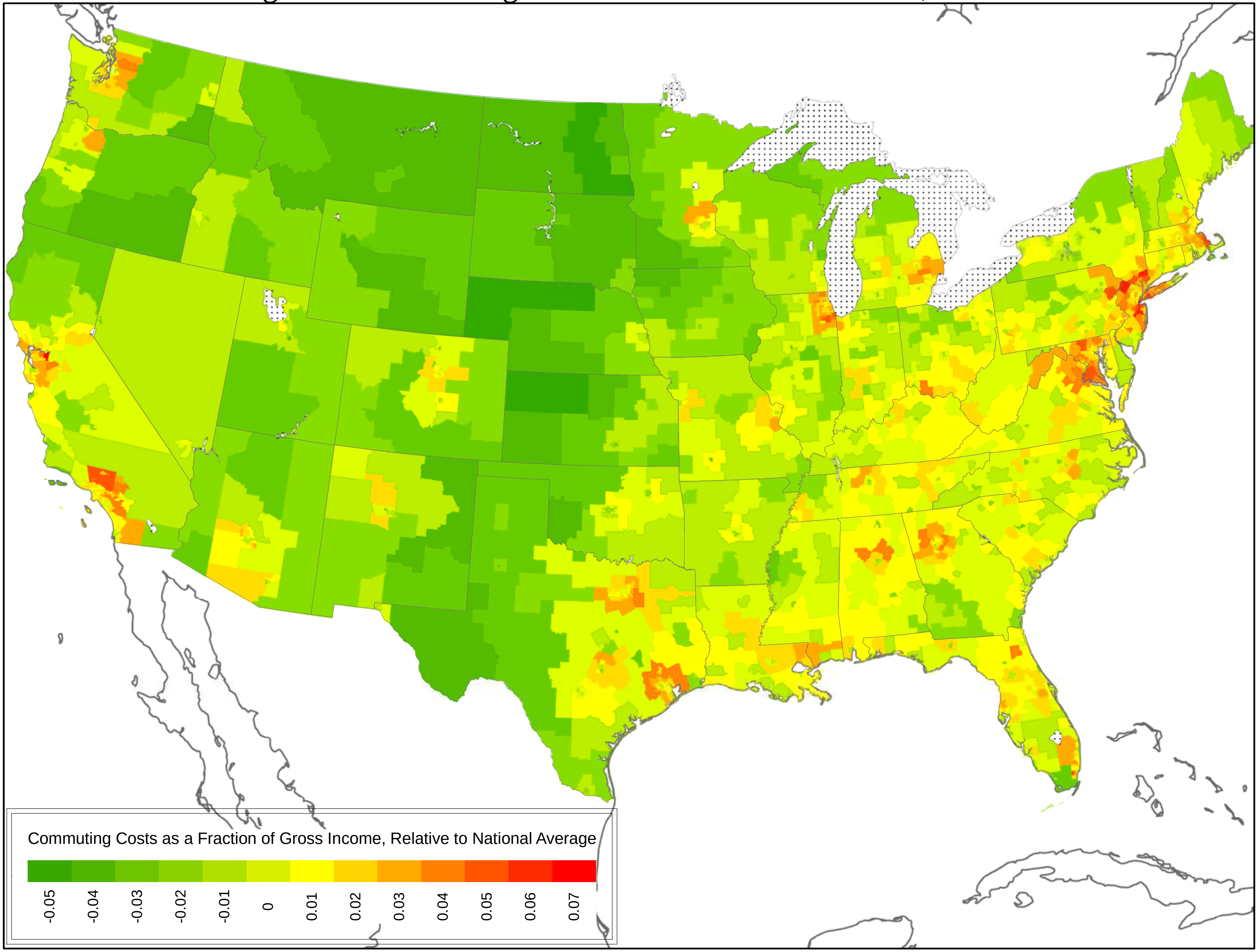
Robust standard errors shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Regressions weighted by population. Variables are described in the Appendix, including Appendix Table A6.

# Figure 1: Wages Estimated by Workplace or by Residence

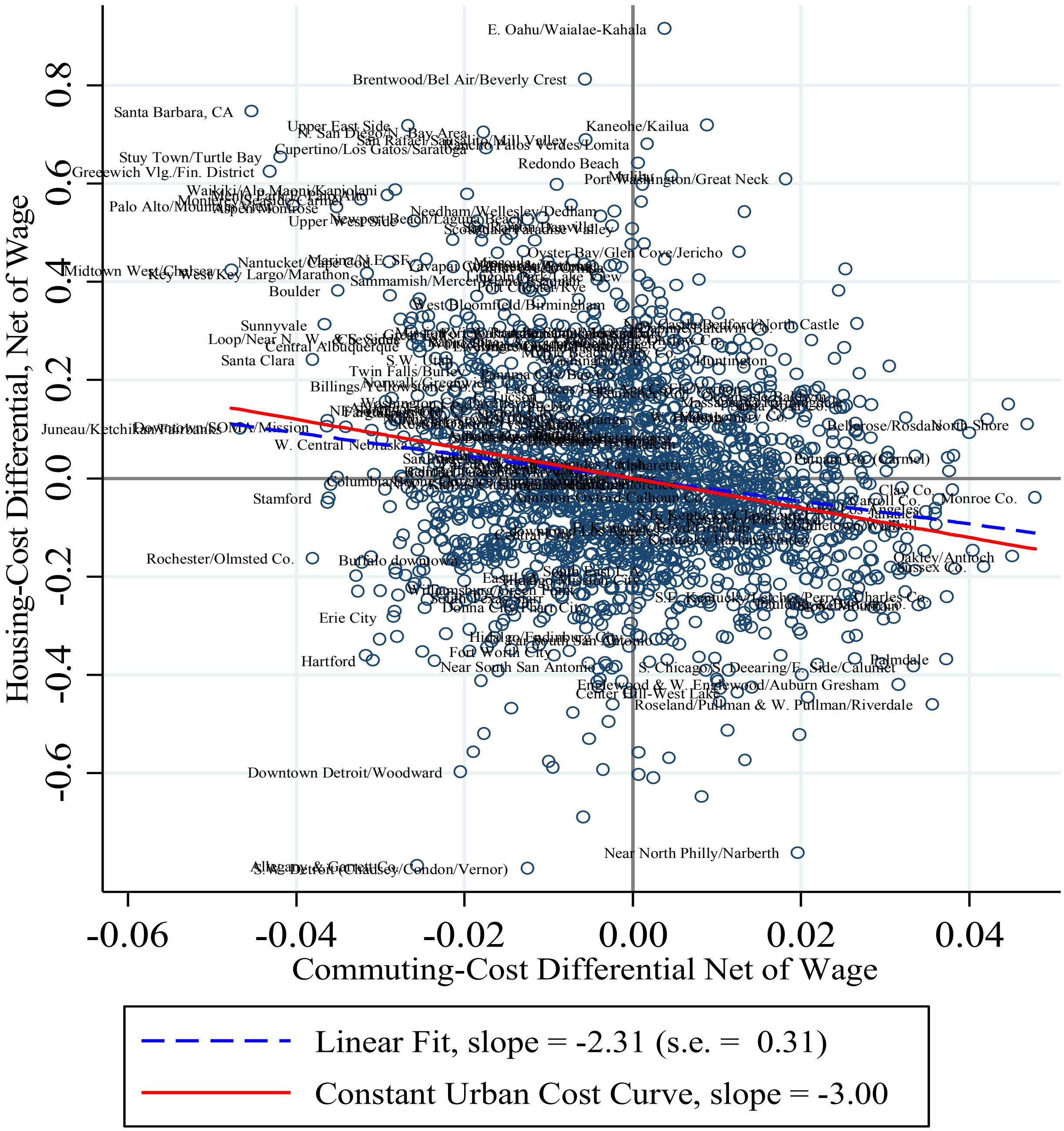



Unit of observation is the residential PUMA.

Figure 2: Commuting Costs across the United States, 2000

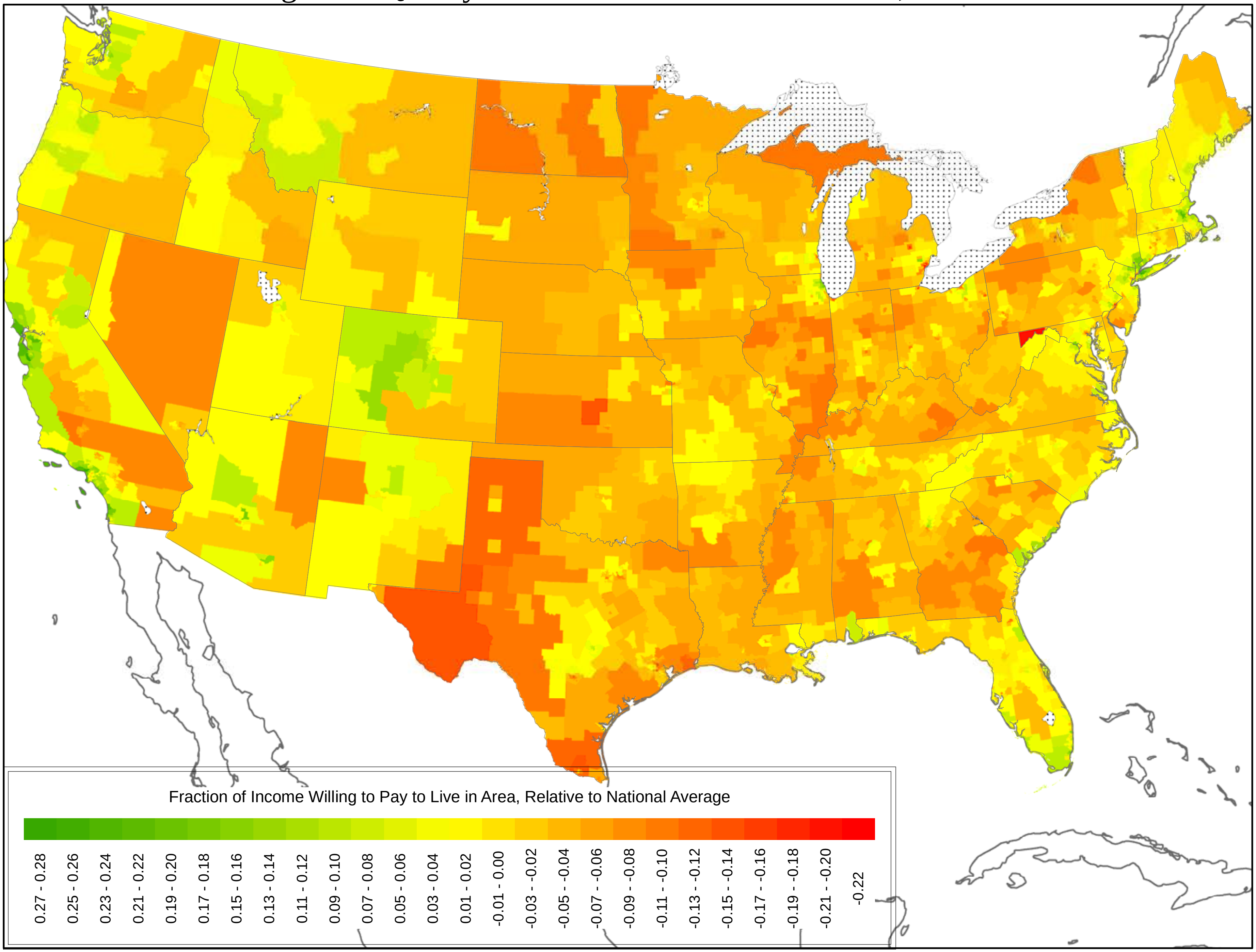


## Figure 3: Housing and Commuting Costs

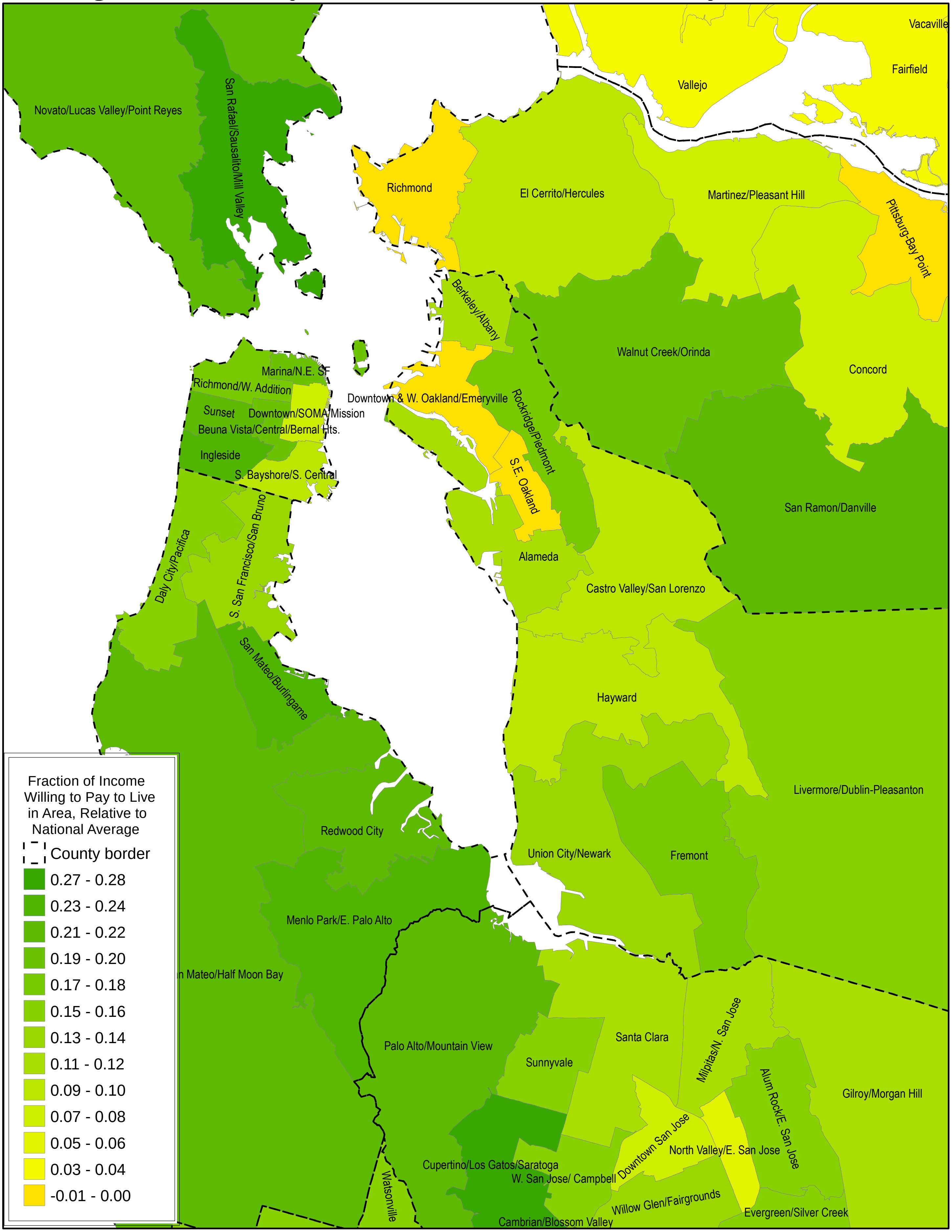



Housing and commuting-cost differentials are residuals from separate regressions on workplace wage levels. Nome/Barrow/Other Alaska left out of scatter plot.

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

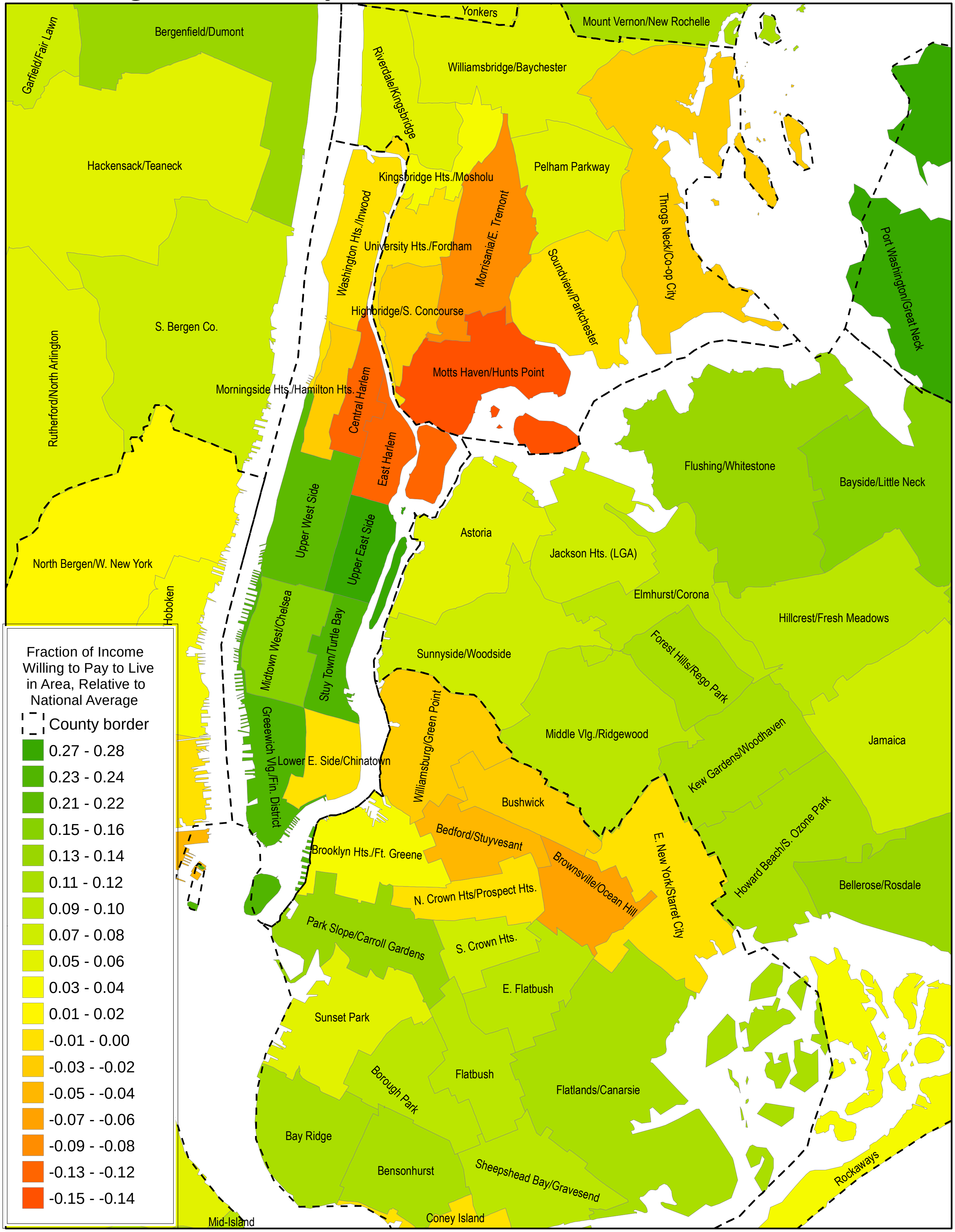


Figure 5C: Quality of Life in Detroit and Southeast Michigan, 2000

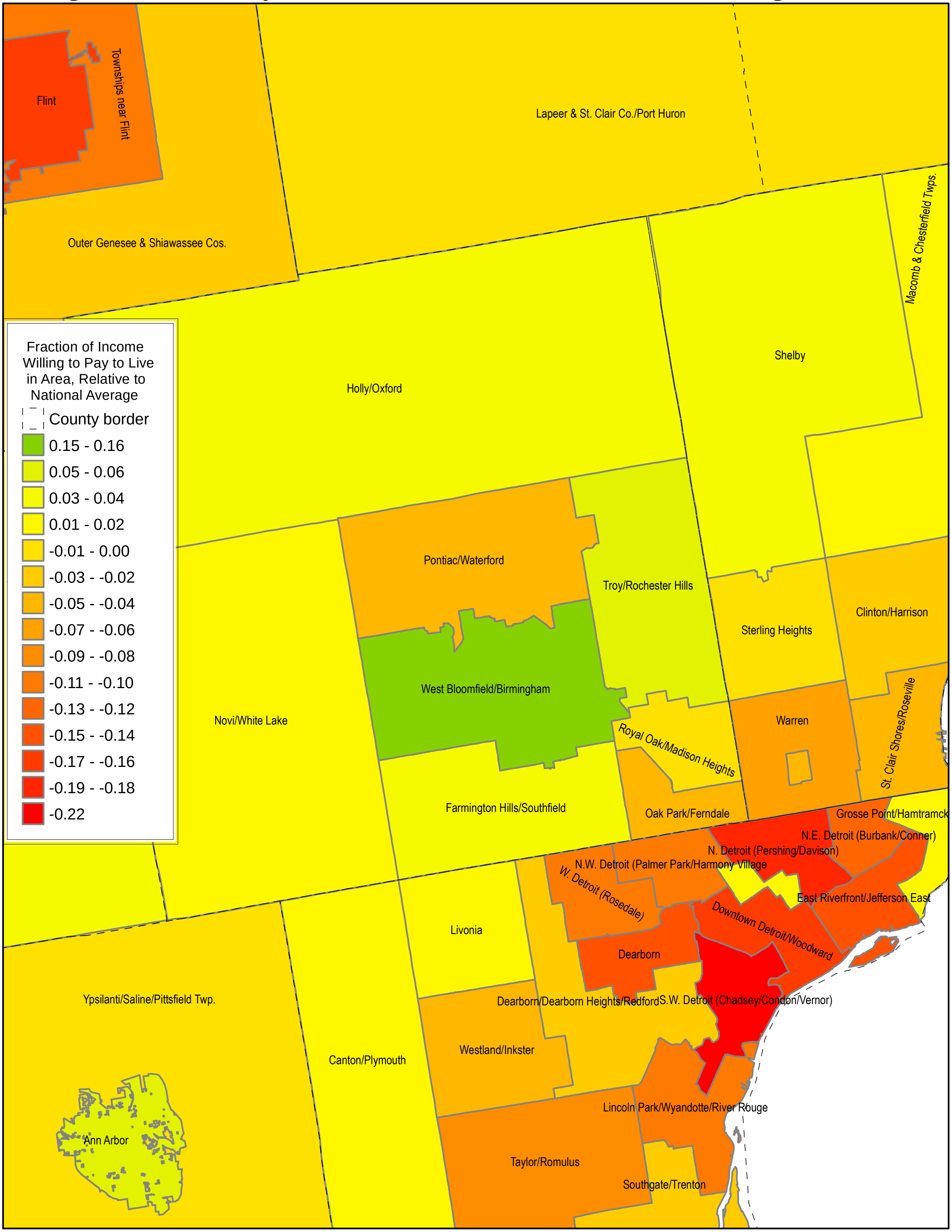
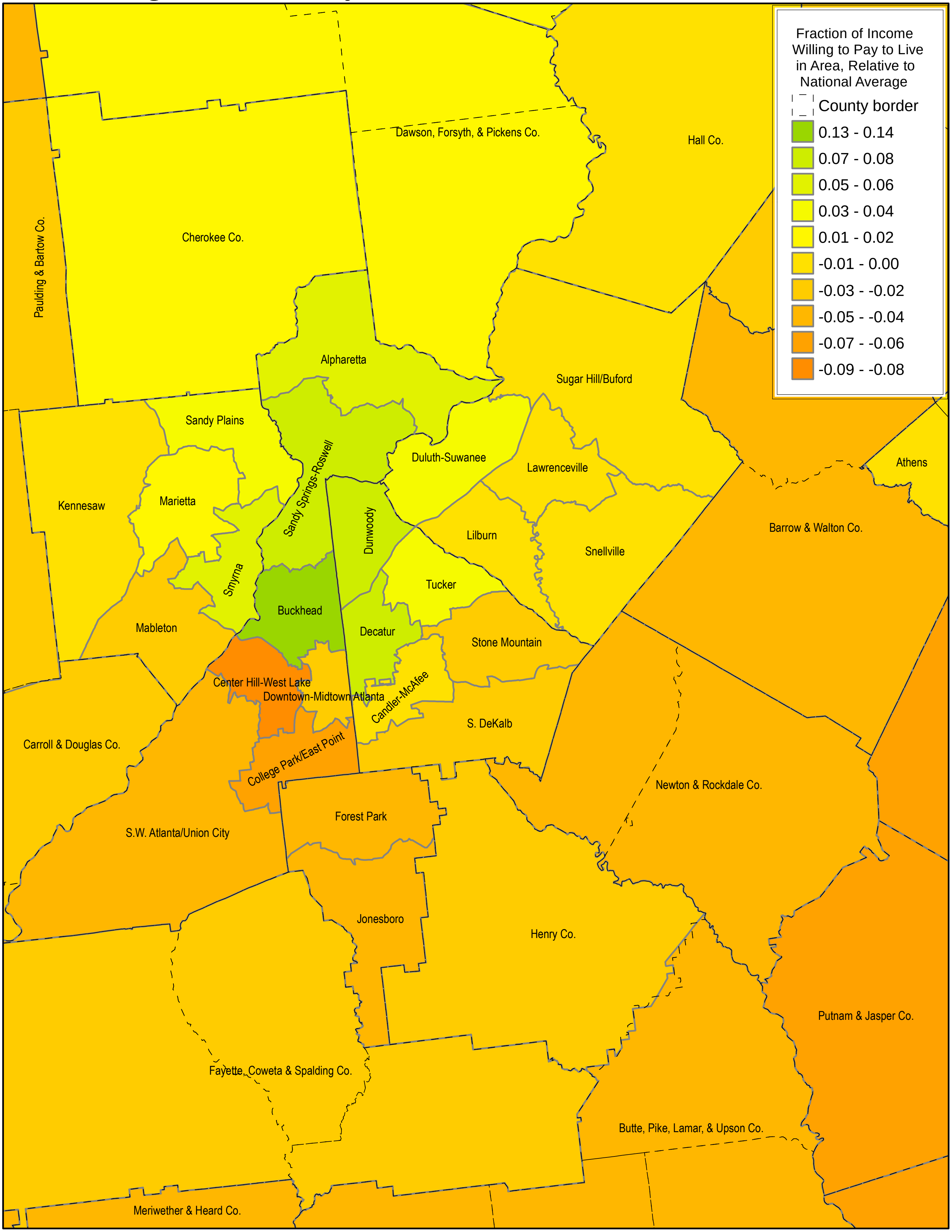


Figure 5D: Quality of Life in and around Atlanta, 2000



# Appendix - Not for Publication

## A Wage, Housing-Cost, and Commuting-Cost Data and Estimation

United States Census data from the 2000 Integrated Public-Use Microdata Series (IPUMS), from Ruggles et al. (2004), are used to calculate wage, rent, and commuting-time differentials.

Reported differentials are calculated using the logarithm of reported gross rents and imputed rents from housing values. We use occupied units that are not farms or group quarters. The rent differentials are calculated using a set of PUMA indicators and the following set of co-variates

- 9 indicators of building size;
- 9 indicators for the number of rooms, 5 indicators for the number of bedrooms, number of rooms interacted with number of bedrooms, and the number of household members per room;
- 2 indicators for lot size;
- 7 indicators for when the building was built;
- 2 indicators for complete plumbing and kitchen facilities;
- an indicator for commercial use;
- an indicator for condominium status (owned units only).

We run our regression with household weights. Appendix Table A2 repeats columns 1 and 2 from Table 1, while column 3 adds the two together to determine a "raw" index, similar to what would be available in an index available from aggregated data. Column 5 presents the fraction that are renting. Columns 5 and 6 describe the variation from indices using only rents or only housing prices: the two appear fairly similar. Column 7 describes an index that weighs housing units by their observable quality.[27] Columns 8 and 9 report household size and time spent in dwelling, revealing fairly little variation across PUMAs. Columns 10 and 11 show how buildings in more central and denser areas tend to be older and have fewer rooms.

The wage differentials are calculated for workers ages 25 to 55, who report working at least 30 hours a week, 26 weeks a year. The wage differentials are found by regressing log hourly wages on individual covariates and indicators for which PWPUMA a worker works in, using the coefficients on these indicators. The covariates consist of

[27] We calculate a value-adjusted weight by multiplying the census-housing weights by the predicted value from this first regression using housing characteristics alone, controlling for PUMA. A second regression is run using these new weights for all units, rented and owner-occupied, on the housing characteristics fully interacted with tenure, along with the PUMA indicators, which are not interacted. The house-price differentials are taken from the PUMA indicator variables in this second regression. As with the wage differentials, this adjusted weighting method has only a small impact on the measured price differentials.

- 12 indicators of educational attainment;
- a quartic in potential experience, and potential experience interacted with years of education;
- 9 indicators of industry at the one-digit level (1950 classification);
- 9 indicators of occupation at the one-digit level (1950 classification);
- 4 indicators of marital status (married, divorced, widowed, separated);
- an indicator for veteran status, and veteran status interacted with age;
- 5 indicators of minority status (Black, Hispanic, Asian, Native American, and other);
- an indicator of immigrant status, years since immigration, and immigrant status interacted with black, Hispanic, Asian, and other;
- 2 indicators for English proficiency (none or poor).

All covariates are interacted with gender.

We run our regression with census-person weights. In columns 1 through 3, Appendix Table A3 repeats the first three measures from Table 1. Column 4 reports the difference between the workplace and residential measures, showing them be negative in central cities and in non-metro areas and positive in the suburbs, suggesting selection according to unobserved skills in the same direction. Column 5 describes raw variation in wages, not controlling for skills. Raw wages are higher in the more skilled suburbs, even though the wage effects are the same. Column 6 reports the variation that would occur if PWPUMAs are used instead of regular PUMAs: this accounts for roughly half of the variance between the workplace and residential measures. Column 7 reveals that almost half of commuters work in a PWPUMA outside the one they reside in; this is especially true if they live in the suburbs. Column 8 measures the wage index weighting workers by the wage predicted by their non-location characteristics, producing nearly identical results.[28] Column 9 corrects for inter-state migration using the methods outlined in Dahl (2002), which also makes little difference.[29]

We calculate commuting-time differentials in a similar manner. The sample restriction is the same as that used for the wage differential calculation, except that those with missing commute time are dropped from the sample. The individual covariates for the commute time regression are

[28] We weight using the single-index of ”skill” that a worker has. From the regressions a predicted wage is calculated using individual characteristics alone, controlling for PWPUMA, to form a new weight equal to the predicted wage times the census-person weight. These new income-adjusted weights are used so workers can be weighted by their income share. The new weights are then used in a second regression, which is used to calculate the PUMA wage differentials from the PWPUMA indicator variables.

[29] To correct for selection effects on our wage estimates due to inter-state migration we control for the probability of moving from the state of birth to the current state, as well as the probability of staying in the state of birth, by category according to various demographic characteristics. We use the exact same categories as Dahl for movers (20 for each state) and stayers (70). We also add a separate mover category/”birth-state” for those born outside the US. As Dahl only used male, white, and ages 25-34, we create 12 times the number of original categories to account for female, non-white, and age categories 35-44, and 45-55. To identify the constants across states, we constrain the coefficients to be the same across states, unlike in Dahl. Accounting for selection through inter-state migration had only tiny effects on our wage estimates.

the same as those used for wages, except that they include four variables for the presence and number of children, total and under 6. We calculate PUMA commute-time differentials from the coefficients of the PUMA indicator variables, using the proper transformation for square roots to get the analog of df/f.

Commuting mode proportions are estimated for all PUMAs using a linear probability model with US Census Data. Mode of transportation to work is split into four broad categories; travel to work by own automobile, carpool, public transportation, and a no-cost method. The public transportation category includes bus, streetcar, rail, subway, and ferry. The no-cost methods are working from home, walking, biking, and other. Binary variables for these four categories are separately regressed on 2071 PUMA dummies and the same set of variables used for commute times.

The resulting estimated probabilities fall between 0 and 1 except for a small number of PUMAs all in Texas, which have tiny negative numbers. We decided against making any adjustments to negative numbers as they were tiny and had negligible effects on the estimates.

Table A4 reports various measures of commuting and associated statistics. There are small differences in Column 1 with the full cost of commuting being highest in the densest areas and higher in the suburbs compared to central city and non-metro areas. Column 2 shows the same pattern in time costs, but with much starker differences. People in the suburbs pay a much higher cost for commuting than other areas. Furthermore, Column 3 shows there is little variation in commuting time across areas predicted by the workforce composition. Material costs, Column 6, tend to be higher in the suburbs, where more people drive, and have longer commutes. Variations in those driving and using transit are due more to variation across metros than within them reinforcing ideas of certain cities being more driving friendly than others.

# B Amenity Data

**Heating and cooling degree days** are measurements used to estimate amounts of energy required to maintain comfortable indoor temperature levels. Daily values are computed from each day's mean temperature ($\frac{max+min}{2}$). Daily heating degree day values are equal to $\max\{0, 65-meantemp\}$ and daily cooling degree day values are $\max\{0, meantemp - 65\}$. Annual degree days are the sum of daily degree day values over the year. The data here refer to averages from 1970 to 2000 (National Climactic Data Center 2008).

**Sunshine** is measured as average percentage of possible. This data set contains information on sunshine as percent of possible sunshine received, by month, for 156 stations in the contiguous United States. The total time that sunshine reaches the surface of the earth is expressed as the percentage of the maximum amount possible from sunrise to sunset with clear sky conditions. (National Climactic Data Center 2008)

**Inverse Distance to Coast** is equal to one over the distance in miles from the population-weighted centroid of the PUMA to the nearest coastline of an Ocean or Great Lake. Coded by author.

**Average Slope of Land** measures the average slope of the land according to census tract data. We used high-resolution elevation data from the Global 30 Arc Second Elevation Data (GTOPO30) digital elevation model (DEM) available from the United States Geological

Survey. These data are set on a high resolution grid of roughly 11 kilometers. We mapped the girded elevation data to our PUMA geography averaging the value of all grid points falling within the boundary of each geography. The slope is computed using the average maximum technique, where the slope at each grid point is the maximum rate of change of elevation from that grid point to its eight neighbors. Due to the high resolution of the data, all geographic units had at least one grid falling inside its boundary. (United States Geological Survey)

**Murder Rate** is the average number of murders per 1,000 inhabitants. It is reported at the county level. (FBI 2000 Uniform Crime Reports)

**Bars and restaurants** data are the number of establishments classified as eating and drinking places, NAICS 722. (County Business Patterns 2000).

**School Revenues per Student** data is at the county level and applies to public schools. (2000 Common Core)

Table A6 reports how these amenities are distributed by area type and density classifications. Panel A shows that central city areas are closer to the coast, have higher murder rates, and more restaurants and bars. Suburban areas have higher public school revenues per student. Panel B splits the US by population density and shows that denser areas have higher school revenues per student, higher murder rates, a greater frequency of restaurants and bars, and are located closest to the coasts. Panel C compares how different amenities vary across and within metropolitan area. Unsurprisingly, because climate is strongly correlated spatially, natural climate related amenities vary more across metros than within. The higher variation within than across metropolitan areas in restaurants and bars reflects a number of splits, including that between residential and commercial areas. Similar variation pattern in the murder rate suggests that there are unsafe areas in many metro areas, rather than being wholly safe and unsafe metros.

# C Additional Tax Details

## C.1 Tax Advantages for Housing and Local Taxes

We model tax advantages for owner-occupied housing by allowing households to deduct a fraction $\delta \in [0,1]$ of home-good expenditures, $py$, from their federal income taxes, so that taxes paid are $\tau\left(m^j - \delta p^j y\right)$. $\delta$ should be less than 1 as these advantages do not apply to certain taxes (e.g. payroll) or to certain home goods, such as haircuts or restaurant meals. Nor are these advantages available to all workers: many renters and home-owners do not itemize deductions for mortgage interest or local taxes. Ignoring for now commuting and leisure, incorporating the home-good deduction into the income tax, $\tau\left(m - \delta py\right)$, changes the expenditure function to $e(p, u, \tau(m - \delta py); Q) \equiv \min_{x,y}\{x + py + \tau(m - \delta py) : U\left(x, y; Q\right) \geq u\}$. Differentiating the mobility condition and using the envelope theorem yields the log-linearized mobility condition

$$\hat{Q}^j = \left(1 - \delta\tau'\right) s_y \hat{p}^j - \left(1 - \tau'\right) s_w \hat{w}^j \tag{A.1}$$

which replaces (5). As calibrated in Albouy (2008), this reduces the weight on $\hat{p}^j$ from 0.36 to 0.33.

### C.2 Including State Tax Differences

Differences in within-state tax burdens are worth considering as wages and prices can often vary significantly within a state, while state services largely do not. We compute state-tax differentials by multiplying state tax and deduction rates by the wage and price differentials within state

$$d\tau_S^j/m = \tau_S'[s_w(\hat{w}^j - \hat{w}^S) - \delta_S s_y(\hat{p}^j - \hat{p}^S)] \quad \text{(A.2)}$$

where $\tau_S'$ and $\delta_S$ are are marginal tax and deduction rates at the state-level, net of federal deductions, and $\hat{w}^S$ and $\hat{p}^S$ are the differentials for state $S$ as a whole relative to the entire country. These state tax rates incorporate sales as well as income taxes, since sales taxes reduce the buying power of labor income. This tax differential is added to (A.1) above to determine local quality of life.

## D Note on Geography

The 5-percent Public Use Microdata Sample (PUMS) from the 2000 Census contains detail for geographic areas known as Public Use Microdata Areas(PUMAs). These PUMAs are required to contain a minimum population of 100,000 and not cross state boundaries. Any collection of counties, census tracts, minor civil divisions (MCDs) can be defined as a PUMA as well as large incorporated places with a minimum population of at least 100,000.

Place of Work Public Use Microdata Areas (POWPUMAs or PWPUMAs) were created to publish information about work location. These areas use the 5-percent PUMAs as building blocks and contain one or more whole PUMAs. Published information from the Census Bureau claiming that PWPUMAs must include entire counties, outside the New England States, is incorrect. [30] Examples include Washtenaw county in Michigan that contains two place-of-work PUMAs: 03200 containing Ann Arbor and 03300 mapping surrounding areas and Hamilton county in Ohio that contains two place of work PUMAs, 04500 containing Cincinatti, and 4400 the surrounding areas.

In application, many densely populated urban areas are split into multiple PUMAs as the minimum population restriction of 100,000 allows, but may be encompassed by only one or two populous PWPUMAs. For example, NY PWPUMA 03800 encompasses New York county, Manhattan, but is made up of 10 different PUMAs 03801-03810. Cincinatti is one PWPUMA 04500, while the same area is split into three PUMAs 04501-04503.

## E Rankings in Popular Media

"Livability" rankings are common in popular media. These rankings are typically presented as references to assist people making decisions about where to live or buy real estate. The comparisons

[30] Phone and email correspondence with the Geographic Standards Criteria Branch of the U.S. Census Bureau verified that this PWPUMAs definition, that PWPUMAs are constructed to encompass whole counties, is present in several of their publications and is incorrect.

are usually performed at a sub-metropolitan level acknowledging the variation in amenities and prices within cities. Streetadvisor.com relies on crowdsourced reviews written by users for streets, neighborhoods, and cities. Areavibes.com and Silver (2010) apply weighting algorithms to various observable amenities; Silver focuses solely on neighborhoods around New York City.

Somewhat surprisingly, rankings from these various methods sometimes match rankings the approach used here. Streetadvisor ranks Carnegie Hill and Roosevelt Island as the two best neighborhoods in New York City. These two neighborhoods are located in NY PUMA 03805, the Upper East Side, which is the 6th highest rated PUMA in the country in our rankings. Areavibes has Springfield MA, Hartford CT, Detroit MI, and Flint MI as the worst cities to live in; each of the PUMAs that contain these areas are in the bottom 10 percent of our rankings, with the PUMA containing Southwest Detroit being our lowest rated PUMA overall. Silver's (2010) ranking are more difficult to compare to ours as he defines neighborhoods at a much finer level of detail than our PUMA analysis will allow. In his write-up, Silver does point out the difficulty of constructing a ranking with weights on observable amenities; he admits that his rankings are quite sensitive to the weights he chooses. With the crowdsourced reviews on Streetadvisor, the concern is not the weighting but selection, as it is unclear what population decides to take the time to write reviews of neighborhoods. While we are satisfied that our PUMA rankings align with some popular measures, we are partial to our methodology which avoids these issues.

TABLE A2: RENT/HOUSING COST DIFFERENTIALS ACROSS THE U.S: ALTERNATIVE MEASURES AND RELATED STATISTICS, 2000

| | Rental Cost Index (1) | Housing Compo-sition "Quality" (2) | Raw Rent Differenti (1) + (2) (3) | Percent Household Renting (4) | Owned Imputed Rents (5) | Actual Rents (6) | Weighted Rent Index (7) | Household Size (8) | Years in Resi-dence (9) | Number of Rooms (10) | Age of Building (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Central City, Suburban, or non-Metropolitan Area* | | | | | | | | | | | |
| Central City (in Metro) | 0.060 | -0.100 | 0.380 | 0.457 | 0.089 | 0.047 | 0.060 | 2.58 | 10.10 | 5.0 | 38 |
| Suburban (in Metro) | 0.083 | 0.057 | 0.147 | 0.277 | 0.068 | 0.099 | 0.086 | 2.68 | 10.55 | 5.7 | 30 |
| Non-Metropolitan Areas | -0.329 | 0.009 | -0.322 | 0.241 | -0.336 | -0.354 | -0.338 | 2.52 | 11.50 | 5.6 | 33 |
| *Panel B: By Residential Population Density* | | | | | | | | | | | |
| >5,000 per square mile | 0.261 | -0.141 | 0.210 | 0.479 | 0.329 | 0.205 | 0.265 | 2.71 | 10.50 | 4.8 | 41 |
| 1,000-5,000 per square mile | 0.006 | 0.061 | 0.077 | 0.293 | -0.027 | 0.047 | 0.008 | 2.60 | 10.27 | 5.7 | 30 |
| <1,000 per square mile | -0.274 | 0.039 | -0.243 | 0.223 | -0.286 | -0.287 | -0.281 | 2.56 | 11.21 | 5.7 | 31 |
| *Panel C:Standard Deviations* | | | | | | | | | | | |
| All PUMAs | 0.348 | 0.146 | 0.361 | 0.148 | 0.408 | 0.308 | 0.360 | 0.326 | 2.15 | 0.67 | 10.0 |
| Across Metropolitan Areas | 0.302 | 0.071 | 0.298 | 0.073 | 0.351 | 0.267 | 0.310 | 0.199 | 1.67 | 0.39 | 7.0 |
| Within Metropolitan Areas | 0.173 | 0.128 | 0.204 | 0.129 | 0.209 | 0.154 | 0.183 | 0.259 | 1.34 | 0.55 | 7.2 |
| *Fraction of Variance Within* | *0.247* | *0.769* | *0.319* | *0.760* | *0.262* | *0.250* | *0.258* | *0.631* | *0.392* | *0.673* | *0.514* |

Columns 1, 2, 3, 5, 6, and 7 report deviations from the national average; column 4, in proportion, column 8 in persons, 9 and 11 in years. See Table 1 and Appendix for more detail.

TABLE A3: WAGE DIFFERENTIALS ACROSS THE U.S: ALTERNATIVE MEASURES AND RELATED STATISTICS 2000

| | Wage by Work-place (1) | Wage by Resi-dence (2) | Wage by Compo-sition (3) | Workplace minus Residence (4) | Raw Wage Differential (1) + (3) (5) | by Resi-dence PWPUMA (6) | Commute out of PWPUMA (7) | By Work place Weighted (8) | By Work place (Dahl) (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Central City, Suburban, or non-Metropolitan Area* | | | | | | | | | |
| Central City (in Metro) | 0.031 | 0.010 | -0.044 | -0.022 | 0.028 | 0.020 | 0.352 | 0.032 | 0.031 |
| Suburban (in Metro) | 0.032 | 0.051 | 0.034 | 0.019 | 0.041 | 0.043 | 0.487 | 0.032 | 0.031 |
| Non-Metropolitan Areas | -0.141 | -0.158 | -0.021 | -0.016 | -0.152 | -0.154 | 0.310 | -0.140 | -0.138 |
| *Panel B: By Residential Population Density* | | | | | | | | | |
| >5,000 per square mile | 0.108 | 0.085 | -0.061 | -0.023 | 0.095 | 0.097 | 0.440 | 0.107 | 0.107 |
| 1,000-5,000 per square mile | 0.002 | 0.019 | 0.040 | 0.017 | 0.016 | 0.011 | 0.414 | 0.001 | 0.001 |
| <1,000 per square mile | -0.113 | -0.119 | -0.005 | -0.007 | -0.118 | -0.117 | 0.381 | -0.111 | -0.110 |
| *Panel C:Standard Deviations* | | | | | | | | | |
| All PUMAs | 0.127 | 0.145 | 0.104 | 0.055 | 0.139 | 0.134 | 0.205 | 0.125 | 0.124 |
| Across Metropolitan Areas | 0.123 | 0.130 | 0.047 | 0.015 | 0.132 | 0.126 | 0.156 | 0.121 | 0.120 |
| Within Metropolitan Areas | 0.033 | 0.065 | 0.093 | 0.053 | 0.045 | 0.046 | 0.133 | 0.034 | 0.032 |
| *Fraction of Variance Within* | *0.068* | *0.201* | *0.800* | *0.929* | *0.105* | *0.118* | *0.421* | *0.074* | *0.067* |

Columns 1 through 6, 8 and 9 are log differences relative to the national average. Column 7 is a proportion. See Table 1 and Appendix for more detail.

TABLE A4: COMMUTING DIFFERENTIALS ACROSS THE U.S: ALTERNATIVE MEASURES AND RELATED STATISTICS., 2000

| | Full Cost (1) | Time Cost (2) | Compo-sition (3) | Raw Differential (4) | Time Cost (5) | Material Cost (6) | Fraction Driving (7) | Fraction Transit (8) |
|---|---|---|---|---|---|---|---|---|
| *Panel A: Central City, Suburban, or non-Metropolitan Area* | | | | | | | | |
| Central City (in Metro) | -0.003 | -0.010 | 0.005 | -0.001 | -0.001 | 0.037 | 0.848 | 0.099 |
| Suburban (in Metro) | 0.006 | 0.055 | -0.001 | 0.064 | 0.003 | 0.043 | 0.932 | 0.031 |
| Non-Metropolitan Areas | -0.013 | -0.141 | -0.005 | -0.132 | -0.007 | 0.034 | 0.948 | 0.008 |
| *Panel B: By Residential Population Density* | | | | | | | | |
| >5,000 per square mile | 0.006 | 0.106 | 0.006 | 0.115 | 0.005 | 0.041 | 0.814 | 0.130 |
| 1,000-5,000 per square mile | -0.001 | -0.029 | -0.001 | -0.020 | -0.001 | 0.040 | 0.941 | 0.022 |
| <1,000 per square mile | -0.005 | -0.065 | -0.004 | -0.056 | -0.003 | 0.038 | 0.953 | 0.008 |
| *Panel C:Standard Deviations* | | | | | | | | |
| All PUMAs | 0.019 | 0.220 | 0.104 | 0.139 | 0.139 | 0.134 | 0.124 | 0.125 |
| Across Metropolitan Areas | 0.015 | 0.176 | 0.047 | 0.132 | 0.132 | 0.126 | 0.120 | 0.121 |
| Within Metropolitan Areas | 0.012 | 0.132 | 0.093 | 0.045 | 0.045 | 0.046 | 0.032 | 0.034 |
| *Fraction of Variance Within* | *0.399* | *0.360* | *0.800* | *0.105* | *0.105* | *0.118* | *0.067* | *0.074* |

Columns 1, 2, 3, 4 and 5 are deviations from the national average. The rest are proportions. See Table 1 and Appendix for more detail.

TABLE A5: DEMOGRAPHIC CHARACETRISTICS ACROSS THE U.S., 2000

| | Under 18 (1) | Over 65 (2) | Married (3) | In Labor Force (4) | College Degree (5) | Race: Black (6) | Immi-grant (7) |
|---|---|---|---|---|---|---|---|
| *Panel A: Central City, Suburban, or non-Metropolitan Area* | | | | | | | |
| Central City (in Metro) | 0.27 | 0.11 | 0.37 | 0.49 | 0.37 | 0.20 | 0.18 |
| Suburban (in Metro) | 0.28 | 0.12 | 0.45 | 0.51 | 0.38 | 0.09 | 0.12 |
| Non-Metropolitan Areas | 0.28 | 0.14 | 0.46 | 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 | 0.49 | 0.38 | 0.19 | 0.26 |
| 1,000-5,000 per square mile | 0.28 | 0.12 | 0.44 | 0.51 | 0.39 | 0.10 | 0.10 |
| <1,000 per square mile | 0.28 | 0.13 | 0.47 | 0.49 | 0.24 | 0.08 | 0.04 |
| *Panel C:Standard Deviations* | | | | | | | |
| All PUMAs | 0.041 | 0.041 | 0.066 | 0.055 | 0.187 | 0.172 | 0.127 |
| Across Metropolitan Areas | 0.023 | 0.028 | 0.026 | 0.035 | 0.102 | 0.095 | 0.101 |
| Within Metropolitan Areas | 0.035 | 0.029 | 0.060 | 0.042 | 0.156 | 0.143 | 0.077 |
| *Fraction of Variance Within* | *0.729* | *0.500* | *0.826* | *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 text for greater detail.

TABLE A6: AMENITY DISTRIBUTION ACROSS THE U.S., 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.

Figure A1: Residential Rents (Gross or Imputed) across the United States, 2000

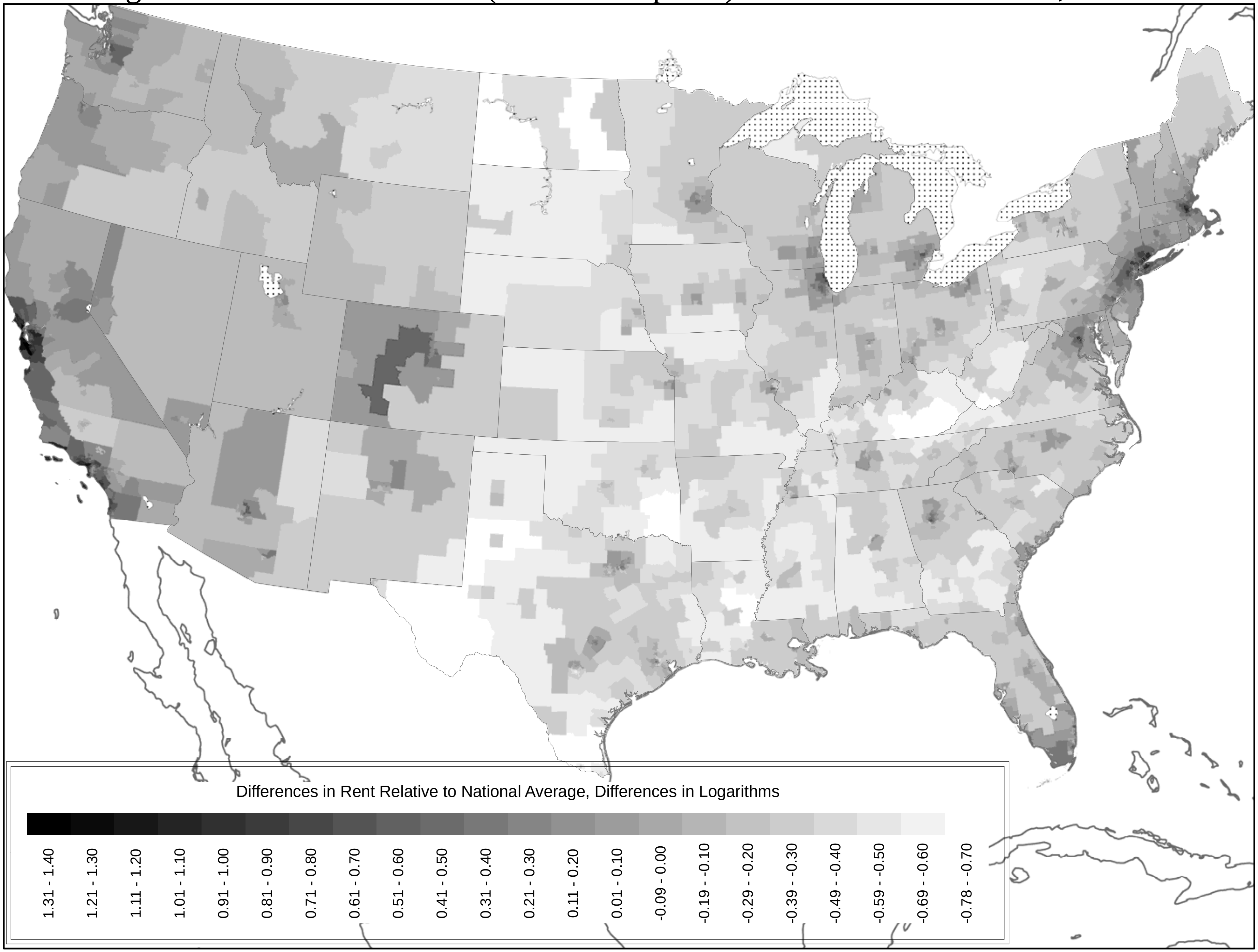


Figure A2: Wage Levels by Workplace across the United States, 2000

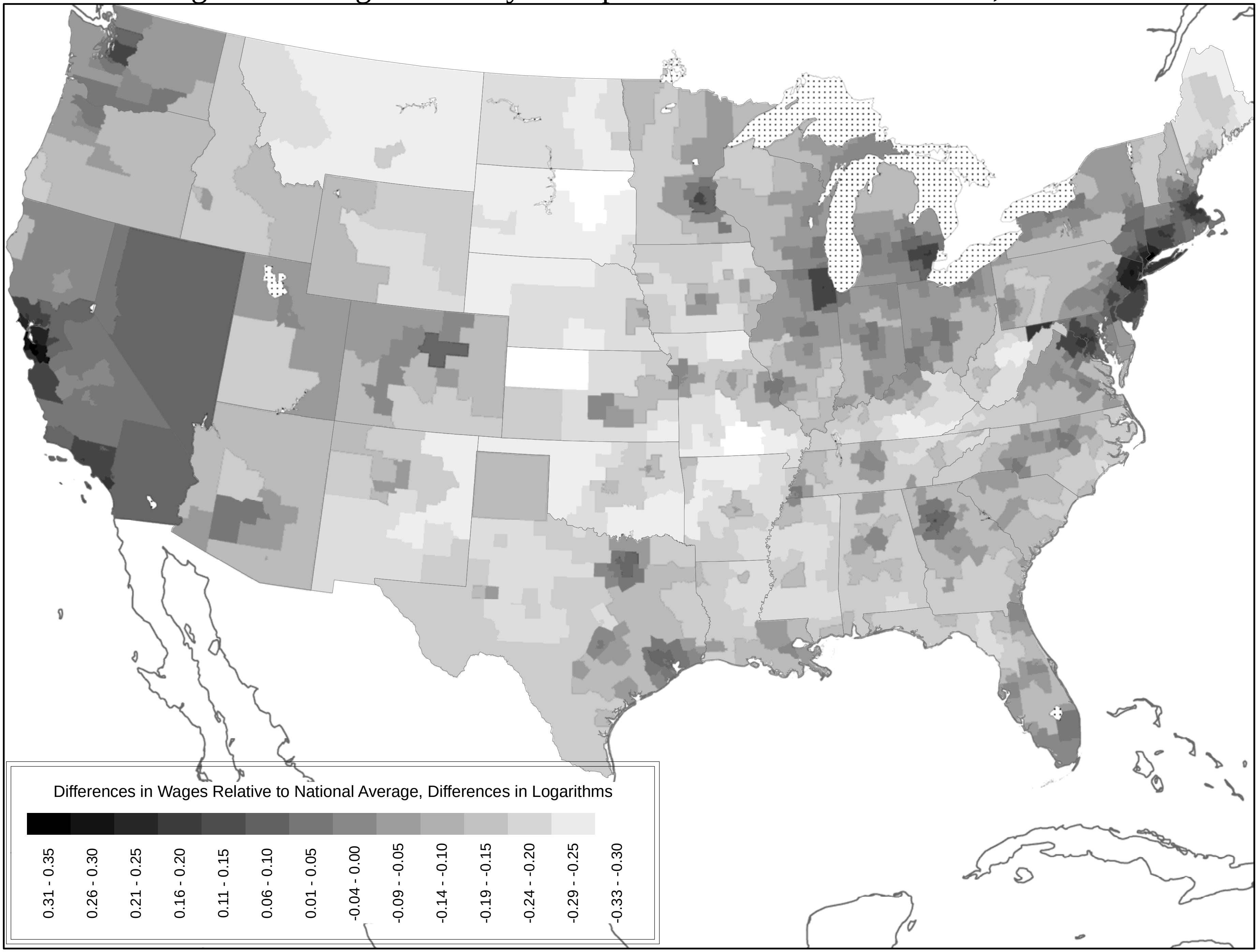
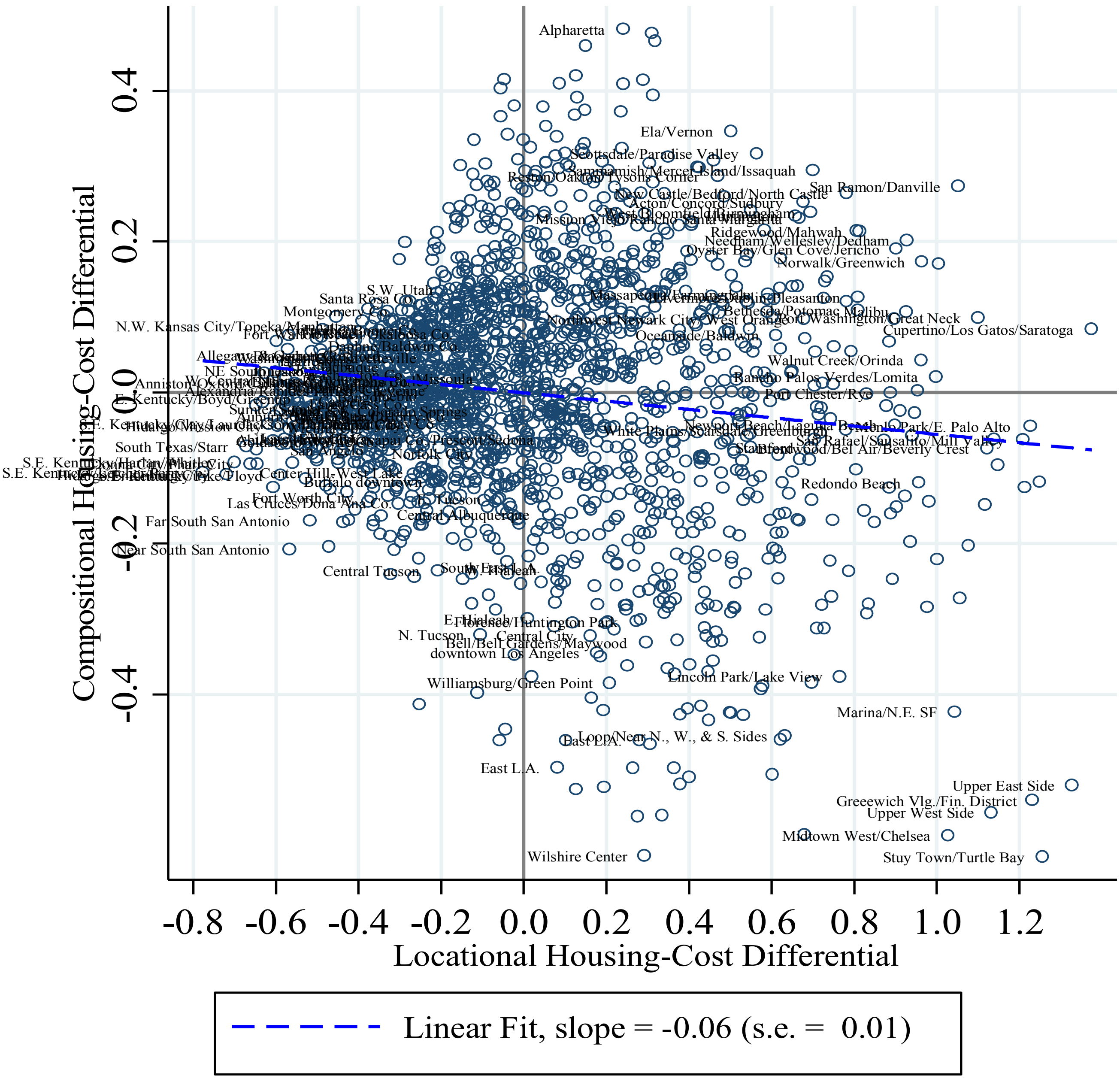


Figure A3: Compositional and Locational Housing Costs




Unit of observation is the residential PUMA.