Differences in Quality of Life Estimates Using Rents and Home Values

Winters, John V

Auburn University at Montgomery

15 April 2010

Differences in Quality of Life Estimates Using Rents and Home Values

John V. Winters*

April 2010

Abstract

Implicit values of amenities and the quality of life in an area can be measured by differences in "real wages" across areas, where real wages are computed as nominal wages adjusted for the cost of living. Computing cost of living differences involves several important issues, most important being how housing prices should be measured. Previous researchers typically have used some combination of rental payments and homeowner housing values. This paper examines differences in quality of life estimates for U.S. metropolitan areas using, alternatively, rents and housing values. We find that the two measures of quality of life are highly correlated. Value-based estimates, however, are considerably more dispersed than rent-based estimates, likely because of the recent bubble in the housing market and because housing values often provide an imperfect measure of the present user cost of housing. Researchers should be cautious in using housing values to construct quality of life estimates.

JEL Classification: R13, R21, R23

Keywords: quality of life; amenities; rents; housing; wages

*Department of Economics, Auburn University at Montgomery, PO Box 244023, Montgomery, AL 36124-4023, Phone (334) 244-3471, E-mail jwinter3@aum.edu

1. Introduction

Researchers, policymakers, and the general public are all interested in differences in the quality of life across areas. Quality of life differences affect individual welfare and have been found to be an important driver of metropolitan population growth (Rappaport 2007, 2009). A number of popular publications have emerged that rank the quality of life across cities and states based on their observable characteristics. Following Rosen (1979) and Roback (1982), economists and other researchers have ranked the quality of life across areas based on compensating differentials in labor, housing, and consumption markets.[1] In other words, the existence of a spatial equilibrium necessitates that workers accept lower "real wages" to live in nicer areas. Computing real wages requires estimating cost of living differences across areas, and doing so is one of the biggest challenges faced by quality of life researchers. Differences in the cost of living across areas are mostly attributable to differences in the cost of housing (Beeson and Eberts 1989), but are also at least partially attributable to differences in the prices of non-housing goods (Gabriel, Mattey, and Wascher 2003). There are two main issues in computing cost of living differences. The first is that good information on non-housing prices is not readily available for all areas. Researchers usually deal with this by either ignoring non-housing prices altogether (e.g., Roback 1982; Blomquist, Berger and Hoehn 1988) or by inferring non-housing prices from housing prices when non-housing prices are not available (e.g., Shapiro 2006; Albouy 2008).[2]

The second major issue in computing cost of living differences is whether housing prices should be measured by rental payments, homeowner user costs based on housing values, or both (Winters 2009). Most studies tend to use a weighted average of rental payments and homeowner

[1] Gabriel and Rosenthal (2004) also develop a method to rank the quality of the business environment across areas.
[2] Alternatively, Gyourko and Tracy (1991) treat non-housing prices as an amenity in wage and housing hedonic regressions.

values, with greater weight given to homeowner values. However, the recent housing bubble has caused rents and homeowner values to diverge considerably (Verbrugge 2008; Garner and Verbrugge 2009). Furthermore, even absent a housing bubble, the ratio of rents to housing values is likely to differ across areas because of different expectations about the future growth of rents (Clark, 1995; Davis, Lehnert and Martin 2008). The value of a house is equal to the expected net present value of the income stream it generates. Areas where rents are expected to grow more quickly should have a lower ratio of rents to values. Therefore, measuring the cost of housing using house values may be inappropriate for estimating the cost of living. Because of this the U.S. Bureau of Labor Statistics (BLS) measures housing prices solely by rents and not values in computing the Consumer Price Index (CPI).[3]

Using a framework similar to Rosen (1979) and Roback (1982), this paper computes quality of life estimates across metropolitan areas of the U.S. for the year 2007. Because values may be an inappropriate measure of housing prices, the preferred estimates compute housing prices using quality-adjusted rents. For comparison, we also compute additional quality of life estimates where housing prices are measured solely by housing values. The two measures of quality of life are very highly correlated, but value-based estimates are considerably more dispersed across areas than the rent-based estimates. That is the value-based estimates report a higher implicit value of amenities in high amenity areas than do the rent-based estimates. This is likely due in large part to the dramatic growth in housing values prior to 2007. However, we also estimate quality of life values for 2000 and find that a similar relationship holds in that year, though to a much lesser extent. Value-based estimates are notably more dispersed than rent-

[3] Winters (2009) also suggests that the relationship between wages and prices across metropolitan areas is consistent with the spatial equilibrium hypothesis when housing prices are measured by rents but not when housing prices are measured by housing values.

based estimates. We conclude that future researchers should use rents and not values when computing estimates of quality of life and amenity values.

2. Theoretical Framework

This section presents a simple model following Rosen (1979) and Roback (1982) that shows that differences in amenity values across cities can be computed from differences in real wages. Firms produce two goods, X_1 and X_2, according to constant returns to scale production functions using labor (N), capital (K), and land (L) and subject to locational differences in productivity due to amenities (Z): $X_i = X_i(N, K, L; Z)$. The marginal products of labor, capital, and land are all non-negative, but increases in amenities can either increase or decrease productivity. The price of capital is determined exogenously in the world market, while the prices of labor (W) and land (P_L) are determined competitively in local markets. In equilibrium, firms earn zero profits and the price of each good is equal to its unit cost of production (C_i):

(1) $C_i(W, P_L; Z) = P_i, \quad i = 1, 2.$

Individual workers maximize their own utility subject to a budget constraint. Utility is a function of goods X_1 and X_2 and location-specific amenities: $U = U(X_1, X_2; Z)$. Workers are mobile across areas, and in equilibrium utility for identical workers is equal across all areas. The indirect utility function can be represented as a function of wages and the prices of X_1 and X_2 given amenities:

(2) $V = V(W, P_1, P_2; Z).$

Taking the total differential of both sides of (2), setting $dV = 0$ so that there are no differences in utility across areas, rearranging, and employing Roy's Identity yields a slight variant of the common equation used to estimate the implicit price of amenities:

(3) $P_Z dZ = X_1 dP_1 + X_2 dP_2 - dW$.[4]

Dividing both sides of (3) by W converts the equation to:

(4) $(P_Z/W)dZ = (P_1X_1/W)d\ \ln P_1 + (P_2X_2/W)d\ \ln P_2 - dln\ W$.

Equation (4) says that the implicit share of wages spent on amenity consumption in an area can be computed from logarithmic differences in real wages across areas, where real wages are equal to nominal wages, W, divided by the cost of living, $\boldsymbol{P}$. Logarithmic differences in nominal wages are represented by the $dln\ W$ term. Logarithmic differences in the cost of living are given by an expenditure share weighted average of the logarithmic differences in the prices of goods one and two. That is, $d\ ln\boldsymbol{P} = (P_1X_1/W)d\ \ln P_1 + (P_2X_2/W)d\ \ln P_2$. The implicit share of wages spent on amenity consumption is thus equal to the negative of log differences in real wages, i.e., $d\ ln\boldsymbol{P} - d\ lnW$.[5] To live in an area with nice amenities workers must accept lower real wages.[6]

3. Empirical Framework and Data

This study computes quality of life estimates for metro areas in the U.S. from the negative of logarithmic differences in real wages. Most previous studies of quality of life differentials across areas try to separately estimate the effect of amenities on wages and housing prices and then aggregate the compensating differentials from these markets to estimate the value of the quality of life in each area.[7] An important limitation to this approach is that important

---

[4] Alternatively, we could have defined the expenditure function and used Shephard's Lemma to obtain an equivalent result as in Albouy (2008).

[5] If the real wage is $W/\boldsymbol{P}$, then the log of the real wage is $ln\ W - ln\ \boldsymbol{P}$.

[6] For non-workers, the implicit price to live in a high quality of life area depends only on the cost of living and not on wages. Thus we would expect retirees and other non-workers to be attracted to areas where amenity values are capitalized more into wages than prices (Chen and Rosenthal 2008).

[7] See Gyourko, Kahn and Tracy (1999) for a review of the literature on quality of life and amenity valuation. Stover and Leven (1992) also discuss a number of important issues related to estimating quality of life.

amenities are unlikely to be completely observed. This would cause the quality of life in areas with nice unobserved amenities to be understated. A further problem concerns how one should account for non-housing prices in this method. Should non-housing price differentials be treated as resulting from amenities as in Gabriel et al. (2003)? What if some of the differential in non-housing prices is due to things other than amenities, such as geographical remoteness? The real wage approach used in this paper does not rely on observed values of amenities and it provides a clear answer as to how non-housing prices should be treated. There are certainly limitations to the real wage approach as well, but it is considered the preferred method for valuing amenities and quality of life in this paper. Similar approaches are also used in Kahn (1995), Albouy (2008), and others.

This paper computes logarithmic differences in nominal wages and housing prices across metropolitan areas using microdata from the 2007 American Community Survey (ACS) and the 2000 Census, both of which are available from the IPUMS (Ruggles et al. 2008). In this study, the geographical unit of analysis is the Combined Statistical Area (CSA) where one exists and the Core Based Statistical Area (CBSA) for areas not part of a CSA. For ease of discussion, we usually just refer to these as metropolitan areas. We only consider CSA/CBSAs that are primarily metropolitan in nature and can be at least partially identified from the IPUMS data. Unfortunately, the IPUMS data do not allow identification of geographic areas with populations less than 100,000. Consequently, the lowest level of identifiable geography, the PUMA, often includes both metropolitan and non-metropolitan areas. We assign each PUMA to a metropolitan area if more than 50 percent of the population of the PUMA is contained within the metropolitan area. This procedure allows us to identify 293 metropolitan areas in both 2000 and

2007.[8] However, it is important to keep in mind that parts of metropolitan areas are often unobservable and our resulting quality of life estimates are subject to some degree of measurement error.

Logarithmic differences in nominal wages across areas are computed by regressing the log of the after-tax hourly wage for worker i in area j on a vector of individual characteristics, X, and a vector of area fixed-effects, α:[9]

(5) $\ln W_{ij} = X_{ij}\beta + \alpha_j + \varepsilon_{ij}.$

The individual characteristics are included to make workers roughly equivalent across areas and include variables commonly found to affect individual wages such as a quadratic specification in potential experience, dummy variables for highest level of education completed, gender, marital status, whether an individual is Black, Hispanic, Asian, or Other, citizenship status, industry, and occupation. These results for the individual characteristics are generally as expected and are available by request. The sample is restricted to workers between the ages of 25 and 61. We use wages net of federal income taxes because the progressive nature of the federal income tax system means that workers in high wage areas pay a higher percentage of their income in federal income taxes than workers in low wages areas (Henderson 1982; Albouy 2008, 2009). However, workers receive the same federal benefits regardless of how much federal taxes they pay. Therefore, workers are ultimately concerned with wages net of federal taxes when making location decisions, and this is what we use in this study. We do not, however, make any

[8] A few small CBSAs are not identified and are not included in this study.

[9] Pre-tax hourly wages (w_{ij}) are estimated by dividing annual wage income by the number of weeks worked times the usual hours worked per week. Federal income taxes are estimated using the federal tax schedule and based on several assumptions. We assume that all married couples file jointly and receive two personal exemptions and non-married persons have a filing status of single and receive one personal exemption. Itemized deductions are assumed to equal 20 percent of annual income, but taxpayers take the standard deduction if it is more than their itemized deductions. Deductions and exemptions are subtracted from annual earnings to estimate taxable income. Tax schedules are then used to compute federal tax liabilities. We next compute the average tax rate for each taxpayer (τ_{ij}), and then multiply the pre-tax hourly wage by one minus the average tax rate to compute after-tax hourly wages ($W_{ij} = w_{ij}(1 - \tau_{ij})$).

adjustment to wages for social security contributions or state and local taxes.[10] The estimated area fixed-effects in (5) represent logarithmic differences in wages across metropolitan areas.

Logarithmic differences in rents and housing values are also based on microdata from the ACS and Census. More specifically, we regress the log of gross rents[11], R, for each housing unit on a vector of housing characteristics, F, and a vector of area fixed-effects, π:

(6) $\ln R_{ij} = F_{ij}\Gamma + \pi_j + u_{ij}.$

We also estimate a similar equation for homeowner housing values:

(7) $\ln V_{ij} = F_{ij}\phi + \lambda_j + \xi_{ij}.$

The housing characteristics included are dummy variables for the number of bedrooms, the total number of rooms, the age of the structure, the number of units in the building, modern plumbing, modern kitchen facilities, and lot size for single-family homes. These results are available upon request. The area fixed-effects from (6) and (7) are used to measure logarithmic differences in rents and housing values across metropolitan areas.

To compute quality of life estimates, we also need to account for non-housing prices. This paper estimates non-housing prices using the ACCRA *Cost of Living Index*. As discussed by Koo, Phillips and Sigalla (2000) and others, there are a number of problems with using the ACCRA data to estimate cost of living differences across areas.[12] However, ACCRA is the single best source of data on interarea differences in non-housing prices available. We combine

[10] Social security contributions could be easily estimated but estimating Social Security benefits is much more difficult. Adjusting wages for state and local income taxes would also require accounting for other taxes and the benefits from public spending that these taxes make possible.

[11] Rents are measured to include certain utilities but exclude a portion of rents attributable to property tax payments based on the effective tax rates of owner-occupied housing. Removing property taxes from rents is based on the assumption that higher property taxes are offset by lowering other state and local taxes (e.g. income, sales, etc.). If this assumption holds, then including property taxes in rents to construct quality of life estimates would cause areas that heavily rely on property taxes to have higher QOL values than they should. As a practical matter, excluding property taxes has only a small effect on QOL estimates for most areas.

[12] ACCRA also reports housing prices and a composite price index that are based primarily on housing values. DuMond, Hirsch and Macpherson (1999) argue that the ACCRA Index is over-dispersed across areas. Winters (2009) suggests that this is primarily because of ACCRA's heavy reliance on housing values.

non-housing prices from ACCRA with the housing price fixed-effects from (6) and (7) to construct two cost of living measures. The rent-based index is a weighted average of rents and non-housing prices excluding utilities with rents given a weight of 0.29 and non-housing prices given a weight of 0.71. Weights are chosen based on calculations from the 2005 Consumer Expenditure Survey suggesting that housing including certain utilities represents 29 percent of average consumption expenditures.[13] The value-based index is computed as a weighted average of housing values and non-housing prices including utilities. Because utilities are now included in non-housing prices, housing values are given a weight of 0.23 and non-housing prices are given a weight of 0.77.

Another issue with the ACCRA data is that they are not available for all metropolitan areas. For areas without ACCRA data on non-housing prices, the rent-based and value-based price indices are imputed based on information from those that are available. For the rent-based index, we regress $ln\boldsymbol{P}$ on the area fixed-effects from (6) along with Census division dummies and metropolitan area population dummies. The coefficients from this regression are then used to predict values of the rent-based index for areas with missing non-housing prices. Missing values for the value-based index are imputed similarly except that they are based on the area fixed-effects from (7).

Once we have constructed rent-based and value-based price indices for every metro area, we then subtract the logarithmic differences in wages from the logarithmic differences in prices to construct the alternative rent-based and housing value-based quality of life estimates. The next section presents these results.

---

[13] Note that this expenditure share for housing differs from official reports of the CES expenditure share for both "Housing" and "Shelter." The housing share based on gross rents used herein includes certain utilities but excludes others and also excludes expenditures for household operations, housekeeping, and household furnishings. The housing share of 0.29 also differs from the official CES tabulations in that homeowner housing expenditures are measured by implicit rents and not by out-of-pocket expenses such as mortgage interest.

4. Quality of Life Estimates

This section presents the results of the quality of life (QOL) estimates and discusses the differences that result from measuring housing prices by rents and by values. This paper differs from most previous quality of life studies because of its emphasis on measuring housing prices by rents instead of housing values. Summary statistics for the rent-based and housing value-based QOL estimates for 2007 are presented in Table 1. Both measures have means close to zero, but the value-based estimates are considerably more dispersed. The standard deviation for the rent-based estimates is 0.058, while the standard deviation for the value-based estimates is 0.094. Similarly, the value-based estimates have a much wider spread between the maximum and minimum values than the rent-based estimates. The spreads between the 90th and 10th percentiles and the 75th and 25th percentiles are considerably smaller than the max-min spread, but for both the value-based QOL estimates continue to be considerably more dispersed than the rent-based estimates.

The quality of life estimates for 2007 are presented in Table 2. Using the rent-based index Honolulu, HI is considered to have the highest quality of life with an estimate of 0.273. The estimate suggests that workers in Honolulu accept roughly 27 percent lower real wages than what they would get from relocating to an average QOL area. Well behind Honolulu is Medford, OR in second with a rent-based QOL estimate of 0.161. Santa Barbara-Santa Maria-Goleta, CA and Burlington-South Burlington, VT are third and fourth with estimates of 0.158 and 0.153, respectively. It would be tedious to discuss the ranking for every area, but a few general observations might be useful. Metropolitan areas in California and Florida tend to do fairly well probably because of their mild winters and proximity to the coast. A few small to mid-size college towns, such as State College, PA and Morgantown, WV, also rank pretty highly.[14] The bottom of the rankings is more mixed but there is some tendency toward interior areas of the country such as in parts of Indiana, Ohio and Texas. Of particular note are a few big cities that rank quite poorly such as Houston-Baytown-Huntsville, TX at 288th and Detroit-Warren-Flint, MI at 290th out of 293.

Though there are some differences, the rankings using the value-based estimates are largely similar. In fact, the Spearman rank correlation between the two series is very high at 0.750.[15] The important difference, though, is that the value-based estimates are considerably more dispersed, especially at the very top of the rankings. Honolulu is still the top ranked area according to the value-based series, but its QOL estimate increases to 0.409. Santa Barbara-Santa Maria-Goleta and Medford swap the second and third positions with estimates of 0.325 and 0.310, respectively. Though there are some exceptions, the value-based estimates for the nicest areas are generally larger than the rent-based estimates. If rents are the appropriate measure of the present user cost of housing, then housing values should not be used as a proxy for rents. Housing values in 2007 are considerably more dispersed across areas than rents, and quality of life estimates based on values are considerably more dispersed than QOL estimates based on rents.

While using housing values to compute QOL estimates is certainly a problem for 2007, one might think that it would not be much of a problem for more “normal” times. After all 2007 was the peak of the housing bubble and values were definitely inflated, especially in areas with an inelastic supply of housing (Glaeser, Gyourko and Saiz 2008). To investigate the extent of

[14] State College is home to Pennsylvania State University and Morgantown is the home of the University of West Virginia. Winters (forthcoming) also shows that college towns are growing faster than other metropolitan areas and suggests that it is because recent student in-migrants often develop friendships, relationships with local employers, and a taste for local amenities and decide to stay in the area after their education is complete.
[15] The correlation for the estimates themselves is also very high at 0.758.

problems from using housing values to measure QOL in more normal times, we next compute rent-based and value-based QOL estimates for 2000. Table 3 reports the summary statistics for 2000. Means are still close to zero and roughly equal for the two series, and the value-based estimates are again more dispersed than the rent-based estimates, though by considerably less than in 2000. The standard deviation is 0.074 for the rent-based estimates and 0.083 for the value-based estimates. The max-min and the 90-10 spreads are also larger for the value-based estimates than the rent-based estimates, though the 75-25 spread is actually slightly larger for the rent-based estimates. Note also that the rent-based QOL estimates became generally less dispersed between 2000 and 2007, while the value-based estimates became more dispersed over the same period.

To conserve space, Table 4 only reports the QOL estimates for the top 20 areas in 2000 according to the rent-based series. Again the value-based estimates are more dispersed, but there is a very high Spearman rank correlation between the two series of 0.893. According to the rent-based estimates, Missoula, MT occupied the top position in 2000 with a QOL estimate of 0.202. Missoula is a small metropolitan area with low population density and nice outdoor recreation amenities that is also home to the University of Montana (Howie, Murphy, and Wicks 2010). A number of other small western areas also ranked highly in 2000 such as Prescott, AZ, Medford, OR and Cheyenne, WY. There are some differences in the QOL rankings between 2000 and 2007, but the rankings are quite highly correlated across the two years. The rent-based estimates in 2000 and 2007 have a Spearman rank correlation of 0.720, and the value-based estimates in 2000 and 2007 have a Spearman rank correlation of 0.714. We have also examined changes in QOL between 2000 and 2007, but the biggest gainers and losers tend to be smaller metro areas.

This may be a legitimate result, but it is probably at least partially due to greater measurement error in QOL for smaller areas and we refrain from making strong inferences.

5. Valuing Amenities

One also might be interested in how the QOL estimates from the previous section are affected by various amenities. To provide some basic insights, this section presents results from regressing the rent-based QOL estimates for 2007 on a number of exogenous amenities. The amenities investigated include the mean January temperature in degrees Fahrenheit, mean hours of sunlight in January, mean July temperature, mean July relative humidity (divided by 100), the percent of land area covered by water (divided by 100), five dummy variables for topography that range from very flat to mountainous, and dummy variables for coastal location on the Atlantic Ocean, Pacific Ocean and Gulf of Mexico. The coastal dummies are constructed by consulting maps. The rest of the variables come from the USDA Economic Research Service (ERS) natural amenities scale. The ERS data are not available for Honolulu, HI, Anchorage, AK and Fairbanks, AK. This reduces the number of metro area observations in this section to 290. Other amenities surely affect the quality of life in an area as well and these variables are not meant to be exhaustive. Summary statistics for the exogenous amenities are reported in Table 5.

The results from regressing the rent-based QOL estimates for 2007 on the exogenous amenities are presented in Table 6 and are generally as one might expect. Warmer January temperatures increase the quality of life in an area with a statistically significant coefficient estimate of 0.0011. In other words, workers are on average willing to accept a 1.1 percent decrease in their real wage to live in an area with a 10 degree Fahrenheit warmer January. January sunlight hours also increase the quality of life with a significant coefficient of 0.0003.

Hotter July temperatures significantly reduce the quality of life in an area with an estimate of -0.0030. July humidity also has a negative coefficient, but the effect is not statistically different from zero. The percent of land area covered with water has a positive coefficient, but is also not statistically significant.

The topography variables suggest that a more mountainous terrain increases the quality of life. The flattest land surface (Topography 1) is the omitted reference group. Topography 3, Topography 4, and Topography 5 are all positive and statistically significant with coefficients of 0.0240, 0.0395, and 0.0534. The dummy variables for location on the Atlantic Coast and Gulf Coast have positive and significant effects on the quality of life with coefficients of 0.0258 and 0.0255, respectively. The Pacific Coast dummy also has a positive coefficient, but the effect is not statistically significant. This, however, should not be interpreted to suggest that the Pacific Coast is not a high quality of life area. Areas on the Pacific Coast tend to have warm winters and mild summers, both of which are highly valued amenities.

6. Conclusion

This paper presents quality of estimates for 293 metropolitan areas in the year 2007 based on differences in real wages across areas, where real wages are defined as nominal wages adjusted for the local cost of living. Households receive utility from the quality of life in an area and are willing to accept lower real wages to live in areas with nice amenities. The spatial equilibrium hypothesis says that utility for identical workers should be equal across locations, and a variant of the Rosen-Roback model shows that quality of life differences across areas can be measured by differences in real wages. An important issue, though, is whether housing prices should be measured by rental payments or owner-occupied housing values. On theoretical grounds, rents are considered the superior measure because housing values are based on the net present value of future rental income and do not necessarily reflect the present user cost of housing. We compute separate quality of life estimates that measure housing prices by rents and by values. The two series are highly correlated, but the housing value-based estimates are considerably more dispersed. This is likely due in large part to the recent housing bubble, but examination of quality of life estimates using data from 2000 shows a similar result, though to a lesser extent. We conclude that future researchers should be cautious in using housing values to measure housing prices in estimating quality of life differences across areas.

References

Albouy, D., 2008. Are big cities really bad places to live? Improving quality-of-life estimates across cities. NBER Working Paper No. 14472.

Albouy, D., 2009. The unequal geographic burden of federal taxation. *Journal of Political Economy* 117(4), 635-667.

Beeson, P.E., Eberts, R.W., 1989. Identifying productivity and amenity effects in interurban wage differentials. *Review of Economics and Statistics* 71(3), 443-452.

Blomquist, G.C., Berger, M.C., Hoehn, J.P., 1988. New estimates of quality of life in urban areas. *American Economic Review* 78(1), 89–107.

Chen, Y., Rosenthal, S.S., 2008. Local amenities and life-cycle migration: Do people move for jobs or fun? *Journal of Urban Economics*, 64(3), 519-537.

Clark, T.E., 1995. Rents and prices of housing across areas of the United States: A cross-section examination of the present value model. *Regional Science and Urban Economics* 25(2), 237-247.

Davis, M.A., Lehnert, A., Martin, R.F., 2008. The rent-price ratio for the aggregate stock of owner-occupied housing. *Review of Income and Wealth* 54(2), 279-284.

DuMond, J.M., Hirsch, B.T., Macpherson, D.A., 1999. Wage differentials across labor markets and workers: does cost of living matter? *Economic Inquiry* 37(4), 577-598.

Gabriel, S.A., Mattey, J.P., Wascher, W.L., 2003. Compensating differentials and evolution in the quality of life among U.S. states. *Regional Science and Urban Economics* 33(5), 619-649.

Gabriel, S.A., Rosenthal, S.S., 2004. Quality of the business environment versus quality of life: Do firms and households like the same cities? *Review of Economics and Statistics* 86(1), 438–444.

Garner, T.I., Verbrugge, R., 2009. Reconciling user costs and rental equivalence: Evidence from the US consumer expenditure survey. *Journal of Housing Economics* 18(3), 172-192.

Glaeser, E.L., Gyourko, J., Saiz, A., 2008. Housing Supply and Housing Bubbles. *Journal of Urban Economics* 64(2), 198-217.

Gyourko, J., Kahn, M., Tracy, J., 1999. Quality of life and environmental comparisons, in *Handbook of Regional and Urban Economics*, Volume 3, eds. Cheshire, P., Mills, E.S. Amsterdam: North Holland, 1413-1454.

Gyourko, J., Tracy, J., 1991. The structure of local public finance and the quality of life. *Journal of Political Economy* 99(4), 774–806.

Henderson, J.V., 1982. Evaluating consumer amenities and interregional welfare differences. *Journal of Urban Economics* 11(1), 32-59.

Howie, P., Murphy, S.M., Wicks, J., 2010. An application of a stated preference method to value urban amenities. *Urban Studies* 47(2), 235-256.

Kahn, M.E., 1995. A revealed preference approach to ranking city quality of life. *Journal of Urban Economics* 38(2), 221-235.

Koo, J., Phillips, K.R., Sigalla, F.D., 2000. Measuring regional cost of living. *Journal of Business & Economic Statistics* 18(1), 127-136.

Rappaport, J., 2007. Moving to nice weather. *Regional Science and Urban Economics* 37(3), 375–398.

Rappaport, J., 2009. The increasing importance of quality of life. *Journal of Economic Geography* 9(6), 779-804.

Roback, J., 1982. Wages, rents, and the quality of life. *Journal of Political Economy* 90(6), 1257-1278.

Rosen, S., 1979. Wage-based indexes of urban quality of life, in *Current Issues in Urban Economics*, eds. Mieskowski, P., Straszheim, M. Baltimore: Johns Hopkins University Press, 74-104.

Ruggles, S., Sobek, M., Alexander, T., Fitch, C.A., Goeken, R., Hall, P.K., King, M., Ronnander, C., 2008. Integrated Public Use Microdata Series: Version 4.0. Minneapolis: Minnesota Population Center.

Shapiro, J.M., 2006. Smart cities: Quality of life, productivity, and the growth effects of human capital. *Review of Economics and Statistics* 88(2), 324-335.

Stover, M.E., Leven, C.L., 1992. Methodological issues in the determination of the quality of life in urban areas. *Urban Studies* 29(5), 737-754.

Verbrugge, R., 2008. The puzzling divergence of aggregate rents and user costs, 1980–2004. *Review of Income and Wealth* 54(4), 671–699.

Winters, J.V., 2009. Wages and Prices: Are workers fully compensated for cost of living differences? *Regional Science and Urban Economics* 39(5), 632-643.

Winters, J.V., Forthcoming. Why are smart cities growing? Who moves and who stays. *Journal of Regional Science*.

Table 1: Summary Statistics for QOL Estimates, 2007

	Rent-based QOL Estimate	Value-based QOL Estimate
Mean	0.003	-0.001
Standard Deviation	0.058	0.094
Max - Min	0.449	0.610
90th - 10th percentile	0.141	0.227
75th - 25th percentile	0.080	0.105

N=293.

Table 2: Quality of Life Estimates and Rankings, 2007

CBSA/CSA Name	Rent-based QOL Est.	Rent-based QOL Rank	Value-based QOL Est.	Value-based QOL Rank
Honolulu, HI CBSA	0.273	1	0.409	1
Medford, OR CBSA*	0.161	2	0.310	3
Santa Barbara-Santa Maria-Goleta, CA CBSA*	0.158	3	0.325	2
Burlington-South Burlington, VT CBSA	0.153	4	0.172	16
State College, PA CBSA*	0.143	5	0.126	30
Fort Walton Beach-Crestview-Destin, FL CBSA*	0.128	6	0.115	33
Chico, CA CBSA*	0.123	7	0.247	7
Morgantown, WV CBSA	0.114	8	0.068	61
Eugene-Springfield, OR CBSA	0.108	9	0.165	17
Bangor, ME CBSA	0.106	10	0.094	41
San Luis Obispo-Paso Robles, CA CBSA*	0.103	11	0.300	4
Coeur d'Alene, ID CBSA*	0.103	12	0.209	11
Anchorage, AK CBSA	0.098	13	0.093	43
Blacksburg-Christiansburg-Radford, VA CBSA*	0.098	14	0.053	66
St. George, UT CBSA	0.093	15	0.092	45
New Orleans-Metairie-Bogalusa, LA CSA	0.092	16	-0.018	148
Bowling Green, KY CBSA	0.090	17	0.022	92
Missoula, MT CBSA	0.090	18	0.154	20
San Diego-Carlsbad-San Marcos, CA CBSA	0.088	19	0.239	9
Pensacola-Ferry Pass-Brent, FL CBSA*	0.088	20	0.035	78
Portland-Vancouver-Beaverton, OR-WA CBSA	0.088	21	0.157	18
Orlando-Deltona-Daytona Beach, FL CSA	0.088	22	0.070	60
Fairbanks, AK CBSA	0.085	23	0.093	44
Panama City-Lynn Haven, FL CBSA*	0.083	24	0.080	53
Hot Springs, AR CBSA	0.082	25	0.036	77
Sarasota-Bradenton-Punta Gorda, FL CSA	0.081	26	0.110	34
Las Cruces, NM CBSA	0.081	27	0.108	35
Salinas, CA CBSA*	0.078	28	0.271	6
Rapid City, SD CBSA*	0.076	29	0.107	36
Ithaca-Cortland, NY CSA	0.075	30	0.024	89
Jacksonville, NC CBSA*	0.075	31	0.022	97
Prescott, AZ CBSA	0.073	32	0.193	12
Fayetteville, NC CBSA	0.073	33	0.007	113
Yuma, AZ CBSA	0.072	34	0.067	62
Miami-Fort Lauderdale-Pompano Beach, FL CBSA	0.072	35	0.098	39
Charlottesville, VA CBSA	0.072	36	0.093	42
Hanford-Corcoran, CA CBSA*	0.071	37	0.139	23
San Jose-San Francisco-Oakland, CA CSA	0.070	38	0.276	5
Portland-Lewiston-South Portland, ME CSA	0.070	39	0.129	27
Charleston-North Charleston-Summerville, SC CBSA	0.068	40	0.040	75
Salem, OR CBSA*	0.068	41	0.126	31
Fort Collins-Loveland, CO CBSA	0.065	42	0.088	47
Logan, UT-ID CBSA*	0.062	43	0.008	111
Lewiston, ID-WA CBSA*	0.060	44	0.081	52

Bend-Prineville, OR CSA*	0.060	45	0.244	8
Los Angeles-Long Beach-Riverside, CA CSA	0.060	46	0.216	10
Colorado Springs, CO CBSA	0.058	47	-0.006	132
Albany-Corvallis-Lebanon, OR CSA*	0.058	48	0.146	21
Williamsport-Lock Haven, PA CSA*	0.058	49	0.043	73
Tallahassee, FL CBSA*	0.056	50	0.036	76
Lawrence, KS CBSA	0.055	51	0.025	87
Lawton, OK CBSA	0.055	52	-0.019	152
Abilene, TX CBSA	0.054	53	-0.058	210
Tucson, AZ CBSA	0.052	54	0.077	55
Bloomington, IN CBSA	0.052	55	-0.021	154
Alexandria, LA CBSA*	0.052	56	-0.037	175
Grand Junction, CO CBSA	0.051	57	0.095	40
Anniston-Oxford, AL CBSA	0.051	58	-0.009	136
Columbus-Auburn-Opelika, GA-AL CSA	0.049	59	-0.016	146
Salt Lake City-Ogden-Clearfield, UT CSA	0.049	60	0.023	91
Port St. Lucie-Sebastian-Vero Beach, FL CSA	0.048	61	0.060	64
Longview, WA CBSA*	0.048	62	0.173	15
Gulfport-Biloxi-Pascagoula, MS CSA	0.047	63	-0.028	159
Spokane, WA CBSA	0.047	64	0.051	68
Springfield, MO CBSA	0.047	65	0.016	101
Asheville-Brevard, NC CSA	0.047	66	0.072	57
Gadsden, AL CBSA*	0.046	67	-0.013	141
Clarksville, TN-KY CBSA*	0.046	68	0.001	120
Elmira, NY CBSA*	0.045	69	-0.029	161
Dothan-Enterprise-Ozark, AL CSA	0.044	70	-0.004	128
Redding, CA CBSA*	0.044	71	0.177	14
Tulsa-Bartlesville, OK CSA	0.044	72	-0.014	145
Lake Havasu City-Kingman, AZ CBSA	0.043	73	0.131	26
Waterloo-Cedar Falls, IA CBSA	0.043	74	0.022	94
Palm Bay-Melbourne-Titusville, FL CBSA*	0.042	75	0.031	81
Myrtle Beach-Conway-Georgetown, SC CSA	0.041	76	0.045	71
Barnstable Town, MA CBSA*	0.040	77	0.186	13
Mobile-Daphne-Fairhope, AL CSA	0.040	78	-0.001	124
Wheeling, WV-OH CBSA*	0.040	79	-0.043	189
Altoona, PA CBSA*	0.040	80	-0.006	133
Sioux Falls, SD CBSA*	0.040	81	0.012	108
Athens-Clarke County, GA CBSA*	0.035	82	0.014	103
Great Falls, MT CBSA*	0.035	83	0.071	59
San Angelo, TX CBSA	0.034	84	-0.044	193
Provo-Orem, UT CBSA*	0.034	85	0.018	99
Wilmington, NC CBSA	0.034	86	0.061	63
Flagstaff, AZ CBSA	0.033	87	0.087	49
Tampa-St. Petersburg-Clearwater, FL CBSA	0.033	88	0.018	98
Dubuque, IA CBSA	0.032	89	0.025	86
Lubbock-Levelland, TX CSA	0.031	90	-0.055	207
Lafayette-Acadiana, LA CSA	0.031	91	-0.013	143
Santa Fe-Espanola, NM CSA*	0.030	92	0.086	50

Pocatello, ID CBSA*	0.029	93	-0.013	142
Hattiesburg, MS CBSA	0.029	94	-0.038	180
Little Rock-North Little Rock-Pine Bluff, AR CSA	0.028	95	-0.020	153
Billings, MT CBSA*	0.028	96	0.017	100
Joplin, MO CBSA	0.028	97	-0.034	170
Fayetteville-Springdale-Rogers, AR-MO CBSA	0.027	98	0.007	112
Ames-Boone, IA CSA	0.027	99	0.013	105
Bellingham, WA CBSA	0.026	100	0.140	22
College Station-Bryan, TX CBSA*	0.024	101	-0.031	164
Jonesboro-Paragould, AR CSA	0.024	102	-0.028	160
Iowa City, IA CBSA*	0.024	103	0.002	119
Boston-Worcester-Manchester, MA-RI-NH CSA	0.024	104	0.132	25
Columbia, MO CBSA	0.023	105	-0.037	177
Idaho Falls-Blackfoot, ID CSA	0.023	106	0.001	121
Lexington-Fayette--Frankfort--Richmond, KY CSA	0.022	107	0.005	116
Jacksonville, FL CBSA	0.022	108	0.000	123
Pittsfield, MA CBSA	0.022	109	0.086	51
Sheboygan, WI CBSA	0.022	110	0.055	65
Montgomery-Alexander City, AL CSA	0.021	111	-0.060	216
New York-Newark-Bridgeport, NY-NJ-CT-PA CSA	0.020	112	0.139	24
Sacramento--Arden-Arcade--Yuba City, CA-NV CSA	0.020	113	0.126	29
Boise City-Nampa, ID CBSA*	0.020	114	0.042	74
Cheyenne, WY CBSA	0.020	115	0.005	117
Eau Claire-Menomonie, WI CSA	0.018	116	-0.005	130
Reno-Sparks-Fernley, NV CSA	0.018	117	0.075	56
Lakeland-Winter Haven, FL CBSA*	0.018	118	-0.004	129
La Crosse, WI-MN CBSA*	0.018	119	0.022	96
Virginia Beach-Norfolk-Newport News, VA-NC CBSA	0.017	120	0.012	107
Lynchburg, VA CBSA*	0.017	121	0.015	102
Valdosta, GA CBSA	0.014	122	-0.034	171
Naples-Marco Island, FL CBSA*	0.014	123	0.126	28
Ocala, FL CBSA*	0.013	124	0.051	67
Brunswick, GA CBSA*	0.012	125	0.045	70
Harrisonburg, VA CBSA	0.012	126	0.024	88
Farmington, NM CBSA	0.011	127	0.087	48
Champaign-Urbana, IL CBSA	0.010	128	-0.030	162
Fargo-Wahpeton, ND-MN CSA	0.009	129	-0.006	131
Dalton, GA CBSA*	0.009	130	-0.014	144
Janesville, WI CBSA	0.009	131	0.006	114
Madison-Baraboo, WI CSA*	0.008	132	0.026	84
Dover, DE CBSA	0.008	133	-0.059	214
Nashville-Davidson--Murfreesboro--Columbia, TN CSA	0.007	134	-0.025	158
Albuquerque, NM CBSA	0.005	135	-0.011	138
Lima-Van Wert-Wapakoneta, OH CSA	0.005	136	-0.003	127
Killeen-Temple-Fort Hood, TX CBSA	0.005	137	-0.058	213
Richmond, VA CBSA	0.005	138	-0.008	135
Bismarck, ND CBSA*	0.005	139	-0.047	201
Huntington-Ashland, WV-KY-OH CBSA*	0.005	140	-0.047	197

Oklahoma City-Shawnee, OK CSA	0.004	141	-0.060	217
Wichita Falls, TX CBSA*	0.004	142	-0.129	280
Parkersburg-Marietta-Vienna, WV-OH CBSA*	0.003	143	-0.042	185
Lincoln, NE CBSA*	0.003	144	-0.022	156
Evansville, IN-KY CBSA	0.003	145	-0.058	212
Hickory-Lenoir-Morganton, NC CBSA	0.002	146	-0.001	125
Battle Creek, MI CBSA*	0.002	147	-0.042	187
Longview-Marshall, TX CSA*	0.001	148	-0.035	174
St. Joseph, MO-KS CBSA	0.001	149	-0.046	195
Seattle-Tacoma-Olympia, WA CSA	0.000	150	0.092	46
Cape Coral-Fort Myers, FL CBSA	-0.001	151	0.027	83
Scranton--Wilkes-Barre, PA CBSA*	-0.001	152	0.002	118
Lancaster, PA CBSA	-0.001	153	-0.007	134
Rome, GA CBSA	-0.002	154	-0.038	178
Amarillo, TX CBSA	-0.003	155	-0.067	225
Fort Smith, AR-OK CBSA	-0.004	156	-0.044	192
Duluth, MN-WI CBSA*	-0.004	157	0.022	93
Wichita-Winfield, KS CSA	-0.004	158	-0.059	215
Philadelphia-Camden-Vineland, PA-NJ-DE-MD CSA	-0.005	159	-0.003	126
Florence, SC CBSA*	-0.007	160	-0.038	182
Tyler-Jacksonville, TX CSA	-0.008	161	-0.074	235
Niles-Benton Harbor, MI CBSA*	-0.008	162	0.033	79
Florence-Muscle Shoals, AL CBSA	-0.008	163	-0.071	232
Danville, VA CBSA*	-0.008	164	-0.087	249
Lafayette-Frankfort, IN CSA	-0.008	165	-0.102	266
Kalamazoo-Portage, MI CBSA	-0.010	166	-0.032	166
Goldsboro, NC CBSA*	-0.010	167	0.013	106
San Antonio, TX CBSA	-0.010	168	-0.066	223
El Paso, TX CBSA	-0.011	169	-0.019	151
Baton Rouge-Pierre Part, LA CSA	-0.012	170	-0.081	244
Harrisburg-Carlisle-Lebanon, PA CSA*	-0.013	171	-0.012	140
Knoxville-Sevierville-La Follette, TN CSA	-0.013	172	-0.034	173
Albany, GA CBSA	-0.014	173	-0.047	200
Washington-Baltimore-Northern VA, DC-MD-VA-WV CSA	-0.015	174	0.006	115
Greenville, NC CBSA	-0.015	175	-0.046	196
Allentown-Bethlehem-Easton, PA-NJ CBSA*	-0.015	176	0.022	95
Denver-Aurora-Boulder, CO CSA	-0.016	177	-0.019	150
Austin-Round Rock, TX CBSA	-0.016	178	-0.066	224
Greenville-Spartanburg-Anderson, SC CSA	-0.017	179	-0.043	188
Birmingham-Hoover-Cullman, AL CSA	-0.017	180	-0.080	241
Minneapolis-St. Paul-St. Cloud, MN-WI CSA	-0.017	181	-0.022	155
Cedar Rapids, IA CBSA	-0.017	182	-0.033	167
Greensboro--Winston-Salem--High Point, NC CSA	-0.017	183	-0.051	206
Savannah-Hinesville-Fort Stewart, GA CSA	-0.017	184	-0.043	190
Modesto, CA CBSA*	-0.018	185	0.098	38
Jackson, MI CBSA*	-0.018	186	-0.011	139
Binghamton, NY CBSA*	-0.018	187	-0.057	209
Louisville--Elizabethtown--Scottsburg, KY-IN CSA	-0.018	188	-0.025	157

Wenatchee, WA CBSA*	-0.018	189	0.125	32
Corpus Christi-Kingsville, TX CSA	-0.019	190	-0.114	272
Laredo, TX CBSA*	-0.019	191	-0.034	172
Yakima, WA CBSA*	-0.019	192	0.031	80
Texarkana, TX-Texarkana, AR CBSA*	-0.019	193	-0.073	234
Jackson-Yazoo City, MS CSA	-0.019	194	-0.101	265
Stockton, CA CBSA*	-0.020	195	0.102	37
Syracuse-Auburn, NY CSA	-0.021	196	-0.049	204
Huntsville-Decatur, AL CSA	-0.021	197	-0.071	231
Bakersfield, CA CBSA	-0.023	198	0.044	72
Atlanta-Sandy Springs-Gainesville, GA-AL CSA	-0.025	199	-0.100	263
Charleston, WV CBSA	-0.025	200	-0.069	230
Phoenix-Mesa-Scottsdale, AZ CBSA	-0.025	201	-0.018	149
Tuscaloosa, AL CBSA	-0.025	202	-0.058	211
Grand Forks, ND-MN CBSA*	-0.026	203	-0.081	243
Rochester-Batavia-Seneca Falls, NY CSA	-0.026	204	-0.057	208
Davenport-Moline-Rock Island, IA-IL CBSA	-0.027	205	-0.031	165
Raleigh-Durham-Cary, NC CSA	-0.027	206	-0.065	221
Omaha-Council Bluffs-Fremont, NE-IA CSA	-0.028	207	-0.063	219
Shreveport-Bossier City-Minden, LA CSA	-0.028	208	-0.085	247
Utica-Rome, NY CBSA*	-0.028	209	-0.066	222
Grand Rapids-Muskegon-Holland, MI CSA	-0.029	210	-0.039	183
Fresno-Madera, CA CSA	-0.029	211	0.071	58
Topeka, KS CBSA	-0.033	212	-0.090	253
Columbia-Newberry, SC CSA	-0.033	213	-0.099	261
Johnson City-Kingsport-Bristol (Tri-Cities), TN-VA CSA	-0.033	214	-0.038	181
Albany-Schenectady-Amsterdam, NY CSA	-0.034	215	-0.033	168
Rochester, MN CBSA	-0.034	216	-0.088	251
Victoria, TX CBSA	-0.034	217	-0.090	254
Hagerstown-Martinsburg, MD-WV CBSA*	-0.035	218	0.013	104
Houma-Bayou Cane-Thibodaux, LA CBSA*	-0.035	219	-0.068	226
Chattanooga-Cleveland-Athens, TN-GA CSA	-0.037	220	-0.048	203
Pittsburgh-New Castle, PA CSA	-0.038	221	-0.061	218
Kansas City-Overland Park-Kansas City, MO-KS CSA	-0.039	222	-0.085	248
Mansfield-Bucyrus, OH CSA	-0.039	223	-0.044	191
Visalia-Porterville, CA CBSA*	-0.040	224	0.050	69
Cumberland, MD-WV CBSA*	-0.041	225	0.000	122
Erie, PA CBSA	-0.041	226	-0.034	169
Casper, WY CBSA*	-0.041	227	-0.048	202
Cleveland-Akron-Elyria, OH CSA	-0.042	228	-0.050	205
Macon-Warner Robins-Fort Valley, GA CSA*	-0.042	229	-0.114	273
Dayton-Springfield-Greenville, OH CSA	-0.043	230	-0.068	227
Johnstown, PA CBSA	-0.044	231	-0.018	147
Bloomington-Normal, IL CBSA	-0.045	232	-0.079	240
Ocean City, NJ CBSA*	-0.046	233	0.154	19
Gainesville, FL CBSA	-0.048	234	-0.041	184
Hartford-West Hartford-Willimantic, CT CSA	-0.048	235	0.009	110
Jefferson City, MO CBSA	-0.049	236	-0.068	228

Augusta-Richmond County, GA-SC CBSA	-0.049	237	-0.087	250
Charlotte-Gastonia-Salisbury, NC-SC CSA	-0.049	238	-0.093	258
Lansing-East Lansing-Owosso, MI CSA*	-0.050	239	-0.083	246
Pueblo, CO CBSA	-0.050	240	-0.047	199
McAllen-Edinburg-Mission, TX CBSA	-0.050	241	-0.101	264
Peoria-Canton, IL CSA	-0.050	242	-0.076	237
Weirton-Steubenville, WV-OH CBSA*	-0.050	243	-0.037	176
Lake Charles-Jennings, LA CSA	-0.051	244	-0.116	276
Fond du Lac-Beaver Dam, WI CSA*	-0.051	245	-0.010	137
Saginaw-Bay City-Saginaw Township North, MI CSA*	-0.052	246	-0.074	236
Roanoke, VA CBSA	-0.053	247	-0.078	239
Sioux City-Vermillion, IA-NE-SD CSA	-0.054	248	-0.094	259
Atlantic City-Hammonton, NJ CBSA*	-0.055	249	0.029	82
Canton-Massillon, OH CBSA*	-0.056	250	-0.042	186
Jackson-Humboldt, TN CSA	-0.058	251	-0.124	279
Springfield, MA CBSA*	-0.059	252	0.023	90
Monroe-Bastrop, LA CSA*	-0.061	253	-0.082	245
Chicago-Naperville-Michigan City, IL-IN-WI CSA	-0.062	254	-0.038	179
Norwich-New London, CT CBSA	-0.062	255	0.010	109
Sumter, SC CBSA	-0.062	256	-0.107	270
Buffalo-Niagara-Cattaraugus, NY CSA	-0.063	257	-0.073	233
Springfield, IL CBSA	-0.064	258	-0.123	278
Waco, TX CBSA	-0.064	259	-0.143	284
Midland-Odessa, TX CSA	-0.064	260	-0.157	288
Green Bay, WI CBSA	-0.064	261	-0.045	194
Columbus-Marion-Chillicothe, OH CSA	-0.065	262	-0.091	255
Rockford-Freeport-Rochelle, IL CSA	-0.066	263	-0.080	242
Muncie, IN CBSA*	-0.066	264	-0.106	269
York-Hanover-Gettysburg, PA CSA	-0.067	265	-0.068	229
Memphis, TN-MS-AR CBSA	-0.069	266	-0.147	286
Danville, IL CBSA	-0.070	267	-0.092	256
Dallas-Fort Worth, TX CSA	-0.071	268	-0.147	287
Indianapolis-Anderson-Columbus, IN CSA	-0.071	269	-0.135	283
Youngstown-Warren-East Liverpool, OH-PA CSA	-0.072	270	-0.099	262
Des Moines-Newton-Pella, IA CSA	-0.073	271	-0.114	274
Terre Haute, IN CBSA	-0.075	272	-0.104	267
St. Louis-St. Charles-Farmington, MO-IL CSA	-0.077	273	-0.108	271
Salisbury-Ocean Pines, MD CSA*	-0.078	274	-0.030	163
South Bend-Elkhart-Mishawaka, IN-MI CSA	-0.083	275	-0.145	285
Merced, CA CBSA*	-0.085	276	0.079	54
Rocky Mount, NC CBSA*	-0.085	277	-0.089	252
Milwaukee-Racine-Waukesha, WI CSA	-0.085	278	-0.047	198
Wausau-Merrill, WI CSA	-0.089	279	-0.076	238
Fort Wayne-Huntington-Auburn, IN CSA	-0.090	280	-0.158	289
Kennewick-Pasco-Richland, WA CBSA	-0.092	281	-0.105	268
Decatur, IL CBSA*	-0.092	282	-0.173	291
Brownsville-Harlingen-Raymondville, TX CSA	-0.093	283	-0.115	275
Beaumont-Port Arthur, TX CBSA	-0.099	284	-0.188	292

Las Vegas-Paradise-Pahrump, NV CSA	-0.099	285	-0.096	260
Appleton-Oshkosh-Neenah, WI CSA*	-0.103	286	-0.064	220
Cincinnati-Middletown-Wilmington, OH-KY-IN CSA	-0.110	287	-0.130	281
Houston-Baytown-Huntsville, TX CSA	-0.116	288	-0.201	293
Toledo-Fremont, OH CSA*	-0.117	289	-0.116	277
Detroit-Warren-Flint, MI CSA	-0.122	290	-0.133	282
El Centro, CA CBSA*	-0.123	291	0.025	85
Owensboro, KY CBSA*	-0.130	292	-0.093	257
Kokomo-Peru, IN CSA*	-0.176	293	-0.158	290

* Indicates that non-housing prices are imputed for the CBSA/CSA.

Table 3: Summary Statistics for QOL Estimates, 2000

	Rent-based QOL Estimate	Value-based QOL Estimate
Mean	-0.005	-0.007
Standard Deviation	0.074	0.083
Max - Min	0.390	0.446
90th - 10th percentile	0.189	0.210
75th - 25th percentile	0.104	0.102

N=293.

Table 4: Quality of Life Estimates and Rankings, 2000

CBSA/CSA Name	Rent-based QOL Est.	Rent-based QOL Rank	Value-based QOL Est.	Value-based QOL Rank
Missoula, MT CBSA	0.202	1	0.224	4
Prescott, AZ CBSA	0.195	2	0.244	2
Morgantown, WV CBSA*	0.182	3	0.102	33
Medford, OR CBSA*	0.178	4	0.247	1
Cheyenne, WY CBSA	0.171	5	0.150	15
Bend-Prineville, OR CSA	0.166	6	0.226	3
Idaho Falls-Blackfoot, ID CSA	0.145	7	0.146	16
Billings, MT CBSA	0.142	8	0.150	14
Flagstaff, AZ CBSA	0.140	9	0.132	20
St. George, UT CBSA	0.140	10	0.142	18
Eugene-Springfield, OR CBSA	0.133	11	0.174	9
State College, PA CBSA*	0.131	12	0.111	29
Santa Barbara-Santa Maria-Goleta, CA CBSA*	0.122	13	0.219	5
Great Falls, MT CBSA	0.121	14	0.160	11
Burlington-South Burlington, VT CBSA	0.118	15	0.141	19
Bismarck, ND CBSA	0.113	16	0.098	34
Lake Havasu City-Kingman, AZ CBSA	0.109	17	0.125	22
Tallahassee, FL CBSA	0.109	18	0.084	40
Charlottesville, VA CBSA*	0.107	19	0.078	43
Columbia, MO CBSA	0.103	20	0.067	51

* Indicates that non-housing prices are imputed for the CBSA/CSA.

Table 5: Summary Statistics for Natural Amenities

	Mean	Std. Dev.	Min	Max
January Temperature	35.729	12.444	3.8	66.7
January Sun	151.081	39.509	52	266
July Temperature	76.197	5.511	61.8	93.7
July Humidity	0.561	0.166	0.14	0.80
% Water Area	0.066	0.115	0.00	0.70
Topography 2	0.134	0.342	0	1
Topography 3	0.107	0.310	0	1
Topography 4	0.221	0.415	0	1
Topography 5	0.128	0.334	0	1
Atlantic Coast	0.072	0.260	0	1
Pacific Coast	0.024	0.154	0	1
Gulf Coast	0.059	0.235	0	1

N=290.

Table 6: Estimated Amenity Values Based on 2007 Rent-Based QOL Estimates

	Coefficient	Standard Error
January Temperature	0.0011**	0.0004
January Sun	0.0003***	0.0001
July Temperature	-0.0030***	0.0010
July Humidity	-0.0010	0.0216
% Water Area	0.0018	0.0313
Topography 2	0.0016	0.0094
Topography 3	0.0240**	0.0111
Topography 4	0.0395***	0.0085
Topography 5	0.0534***	0.0119
Atlantic Coast	0.0258*	0.0136
Pacific Coast	0.0145	0.0249
Gulf Coast	0.0255*	0.0151
Constant	0.1264*	0.0691

Notes: N=290. * Significant at 10%; ** Significant at 5%; *** Significant at 1%.