DISCUSSION PAPER SERIES

IZA DP No. 6703

Differences in Quality of Life Estimates Using Rents and Home Values

John V. Winters

July 2012

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

Differences in Quality of Life Estimates Using Rents and Home Values

John V. Winters
University of Cincinnati
and IZA

Discussion Paper No. 6703
July 2012

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 6703
July 2012

ABSTRACT

Differences in Quality of Life Estimates Using Rents and Home Values*

Quality of life differences across areas can be measured by differences in "real wages", where real wages are computed as nominal wages adjusted for the cost of living. Computing cost of living differences involves several important issues, including how housing prices should be measured. Previous researchers typically have used some combination of rental payments and homeowner housing values, but housing values are forward-looking and may not reflect current user costs. 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 housing bubble 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

Corresponding author:

John V. Winters
Department of Economics
University of Cincinnati
P.O. Box 210371
Cincinnati, OH 45221
USA
E-mail: winterjh@ucmail.uc.edu

* The author would like to thank Barry Hirsch, three anonymous referees, and session participants at the 2009 annual meeting of the Southern Economic Association for helpful comments. Any errors or omissions are solely the responsibility of the author.

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, estimated homeowner user costs based on housing values, or both (Winters 2009). Most studies assume that the true user cost of housing can be

[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.

accurately measured by both housing rents and housing values and, therefore, measure housing prices using a weighted average of rental payments and homeowner values, with greater weight given to homeowner values.[3] However, the recent housing bubble has caused rents and homeowner values to diverge considerably (Verbrugge 2008; Garner and Verbrugge 2009). Even absent a housing bubble, the ratio of housing values to rents is likely to differ across areas because of different expectations about the future growth of rents (Clark, 1995; Davis, Lehnert and Martin 2008). Rental payments reflect the actual *current* user cost of housing for a specific period of time. However, a house is an asset that yields a stream of *future* benefits to its owner. The value of a house is equal to the expected net present value of the *future* benefit stream it generates. Areas where rents are expected to grow more quickly over time should have a higher ratio of current values to current rents because the expected increase in future rental payments is capitalized into current housing values. Therefore, measuring the current user 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). 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. Furthermore, Banzhaf and Farooque (2012) find that local public amenities and income levels are more highly correlated with rents than owner values. This paper suggests that quality of life estimates should base housing prices solely on rents and not on housing values.

[3] A few previous studies have also measured housing prices using either only rents or only housing values instead of a combination of the two, but no previous study has examined differences in quality of life rankings that result from measuring housing prices by only rents or only housing values.

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. The preferred estimates compute housing prices using quality-adjusted rents because rents reflect the current user cost of housing but housing values are based on the future stream of benefits provided by the house. For comparison, we also compute quality of life estimates for which 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-based estimates. Rents are superior on theoretical grounds, and we argue that future researchers should use rents and not values when computing estimates of quality of life and amenity values.

The paper proceeds as follows. The next section presents the theoretical framework based on the seminal work of Rosen (1979) and Roback (1982). The third section discusses the empirical approach and data used in this study. A fourth section presents the results for the quality of life estimates. A fifth section examines the effect of quality of life on changes in rents and housing values from 2000 to 2007. A final section concludes.

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

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.[4] 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) $P_Z dZ = X_1 dP_1 + X_2 dP_2 - dW$.[5]

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

[4] Greenwood, Hunt, Rickman, and Treyz (1991) find that although a few areas may be out of equilibrium at a given point in time, spatial equilibrium is not an unreasonable assumption for the most part. Oswald and Wu (2010, 2011), however, find that subjective responses about individual well-being differ across the United States even after controlling for individual characteristics. This may reflect heterogeneous preferences for locations (Krupka and Donaldson 2007) or decreased responsiveness to area-specific demand shocks (Partridge, Rickman, Olfert and Ali 2012). This could affect our ability to accurately estimate implicit amenity prices and rank quality of life across areas.

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

(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., $d\ ln\boldsymbol{P} - d\ lnW$.[6] To live in an area with nice amenities workers must accept lower real wages.[7]

3. Empirical Framework and Data

This study estimates quality of life values 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.[8] An important limitation to this approach is that important 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

---

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

[7] 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).

[8] 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.

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[9], 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.[10]

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.[11] However, it is important to keep in mind that parts of metropolitan areas are often

[9] One potentially important limitation is that high skilled workers may sort into high wage or high quality of life areas, which would bias the estimates. We include detailed controls for observable worker characteristics but some worker characteristics (e.g. innate ability) remain unobservable.

[10] Gabriel and Rosenthal (2004) and Chen and Rosenthal (2008) follow a related approach by computing quality of life estimates in levels (as opposed to logs) by subtracting the local wage premium from the local housing cost premium. Measuring QOL in levels requires assumptions about household labor supply and housing consumption decisions based on sample means. Their approach does not account for non-housing prices and doing so would require some assumption about non-housing consumption presumably based on income or housing consumption.

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

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:[12]

(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 quartic specification in potential experience, dummy variables for highest level of education completed, gender, marital status, whether an individual is Black, Hispanic, Asian, or Other, head of household, part-time or irregularly employed (working less than 35 hours per week or less than 35 weeks during the previous year), citizenship status, industry, and occupation. We would also like to control for other worker characteristics such as firm size and union coverage/membership, but these are not asked in the ACS and decennial census. The 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, individual workers receive the same federal benefits regardless

[12] 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 ($W_{ij} = w_{ij}(1 - \tau_{ij})$).

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. Albouy (2009) argues that federal income tax rates should be indexed to local wages and that failing to do so significantly reduces economic activity in high wage areas because the additional tax burden makes those areas less desirable to potential migrants. This reduces local employment levels and local land and housing prices and generates locational inefficiencies. Albouy (2008) argues that failing to account for geographic differences in federal taxes causes quality of life estimates to be significantly undervalued in high wage areas such as big cities. We do not make any adjustment to wages for social security contributions or state and local taxes.[13] 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[14], 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,

[13] 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.

[14] 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.

modern kitchen facilities, and lot size (available only for single-unit buildings). 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*. ACCRA works with local chambers of commerce to collect local prices quarterly for 57 goods and services intended to form a representative basket of typical consumer expenditures. Individual prices are then aggregated for each area to create a composite price index and six sub-indices including groceries, transportation, healthcare, miscellaneous goods and services, housing and utilities. 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. In particular, DuMond, Hirsch and Macpherson (1999) argue that the ACCRA Composite Index is significantly over-dispersed across areas. Winters (2009) suggests that this is primarily because of ACCRA's heavy reliance on housing values for the housing index, but there are other issues as well. That said, ACCRA is the single best source of data on interarea differences in non-housing prices available and is used in this study.

We combine 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. Non-housing prices are computed as a weighted average of the ACCRA sub-indices for groceries, transportation, healthcare, and miscellaneous goods and services. 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.[15] 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 based on CES expenditure shares.

Note that this paper assumes constant expenditure shares for housing and non-housing goods, which is consistent with Cobb-Douglas utility and an elasticity of substitution equal to one.[16] Some readers might find this assumption overly restrictive, but Davis and Ortalo-Magné (2011) examine the 1980, 1990, and 2000 decennial census data and find that the expenditure share for housing is fairly constant over time and argue that Cobb-Douglas utility cannot be rejected. Though there is no consensus on the "true" elasticity of substitution between housing and non-housing, a few other studies have found similar results. Ogaki and Reinhart (1998) find an elasticity of 1.17 that is not statistically different from one at the 5% significance level and Piazessi, Schneider, and Tuzel (2007) report estimates of 0.77 and 1.24 for two different time periods, neither of which is statistically different from one.

Another issue with the ACCRA data is that they are not available for all areas. For metropolitan areas with no ACCRA data on non-housing prices, the rent-based and value-based price indices are imputed based on information from those that are available.[17] For the rent-based index, we regress $ln\boldsymbol{P}$ on the area fixed-effects from (6) along with Census division

[15] 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.

[16] An elasticity of substitution less than (greater than) one would imply a higher (lower) expenditure share for housing in areas with relatively high housing prices.

[17] A related problem is that prices are measured at the sub-metropolitan level, but data are not generally available for all areas within a metropolitan area. If sub-metropolitan areas for which prices are reported are not representative of places in the same metro for which prices are not reported, the average price level for the metro area will be measured with error.

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.

4. Quality of Life Estimates

This section presents the results of the quality of life (QOL) estimates and discusses the differences that result from separately 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 solely by rents instead of using a combination of rents and 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 by construction, 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 0.093. 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 90^{th} and 10^{th} percentiles and the 75^{th} and 25^{th} 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 2007 quality of life estimates for the top 20 cities according to the 2007 the rent-based series are presented in Table 2, and estimates for the additional cities are reported in Appendix Table A. Using the rent-based index Honolulu, HI is considered to have the highest quality of life with an estimate of 0.266. 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 0.162. Santa Barbara-Santa Maria-Goleta, CA and Burlington-South Burlington, VT are third and fourth with estimates of 0.156 and 0.154, respectively. It would be tedious to discuss the ranking for every area, but a few general observations are 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.[18] Winters (2011a) examines the effects of a large number of amenities on metropolitan area quality of life and finds that among other things a nice climate, a mountainous topography, a highly educated population and a strong presence of higher education institutions have significantly positive effects on quality of life.[19] 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 289th and Detroit-Warren-Flint, MI at 290th out of 293.

[18] State College is home to Pennsylvania State University and Morgantown is the home of the University of West Virginia. Winters (2011b) 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.

[19] Winters (2011) also finds mixed results for some other common (dis)amenities such as crime, pollution, commute times, population density, and city size.

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 0.746.[20] 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 0.402. Santa Barbara-Santa Maria-Goleta and Medford swap the second and third positions with estimates of 0.323 and 0.311, respectively. Though there are some exceptions, the value-based estimates for the nicest areas are generally larger than the rent-based estimates. Rents are an appropriate measure of the present user cost of housing, but housing values are not and 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 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 small 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 0.071 for the rent-based estimates and 0.080 for the value-based estimates. The max-min, 90-10, and 75-25 spreads are also larger for the value-based estimates than the rent-based estimates. Note also that the rent-based QOL estimates became generally

[20] The correlation for the estimates themselves is also very high at 0.752.

less dispersed between 2000 and 2007, while the value-based estimates became more dispersed over the same period.

Table 4 reports the QOL estimates for the top 20 areas in 2000 according to the rent-based series; results for the additional areas are available from the author by request. Again the value-based estimates are more dispersed, but there is a very high Spearman rank correlation between the two series of 0.883. According to the rent-based estimates, Prescott, AZ and Missoula, MT occupied the top two positions in 2000 with QOL estimates of 0.195 and 0.194. Prescott is a small metro area in the mountains of central Arizona with fairly mild winters and warm summers. Missoula is also a small metropolitan area with low population density and nice outdoor recreation amenities and is home to the University of Montana (Howie, Murphy, and Wicks 2010). The next three spots and several others in the top 20 are also small areas in the Mountain Census Division.

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 0.740, and the value-based estimates in 2000 and 2007 have a Spearman rank correlation of 0.731. We have also examined changes in QOL between 2000 and 2007. The biggest gainers and losers tend to be smaller metro areas. In particular, several of the smaller metros in the Mountain Census Division saw sizable decreases in quality of life estimates between 2000 and 2007 including Prescott, AZ, Billings, MT and Cheyenne WY. Further inspection (not shown) reveals that the decrease in quality of life estimates for these small metros in the Mountain states was driven largely by an apparent positive productivity shock that increased wages. The relatively short time period and the slow migration of labor to relatively remote areas may cause quality of life to be undervalued in 2007 for these areas. Time will tell if these small mountain areas return to the top of the rankings in future years or if their values in 2000 were actually aberrations from their long run values. An alternative explanation is that the relatively small samples for small metros might lead to sizable measurement error and imprecise estimates. Either way, the differences across years for small metro areas suggest that we should be careful in placing too much confidence in quality of life estimates for small areas in a given year.

Many large dense metro areas saw improved rankings between 2000 and 2007 including Boston (227 to 113), Los Angeles (129 to 52), Miami (123 to 37), New York (173 to 120), Philadelphia (275 to 161), San Jose-San Francisco (86 to 40), and Washington-Baltimore (228 to 187). Honolulu has a population of nearly one million people and saw its quality of life rank increase from number 31 in 2000 to number 1 in 2007. Closer inspection reveals that the QOL increase for many of these cities was driven by increases in housing costs. There were also some notable deteriorations in relative quality of life among fairly large cities including Denver (140 to 182), Phoenix (131 to 208), and Pittsburgh (154 to 222).

One might also be interested in how the quality of life rankings in this paper compare to others in recent studies. Table 5 reports the rent-based and value-based quality of life rankings for the 20 largest metros in 2000 and compares these to the rankings in Chen and Rosenthal (2008) and Albouy (2008).[21] There is no single recent study considered a benchmark, but both Chen and Rosenthal (2008) and Albouy (2008) have received considerable attention recently. Both Chen and Rosenthal (2008) and Albouy (2008) use a combination of rents and housing values to measure housing prices. There are a number of other important differences in how these rankings are constructed including the number of areas that are ranked, so differences are to be expected, e.g., New York is ranked highly by the value-based index and by Albouy (2008)

[21] We are not aware of any other rankings for 2007, so we only compare rankings for 2000.

but ranked poorly by the rent-based index and by Chen and Rosenthal (2008). However, there are also some similarities; San Diego does well across all the rankings and Houston ranks poorly. Not surprisingly, the value-based index tends to be closer to the Chen and Rosenthal (2008) and Albouy (2008) than the rent-based index.

5. Effects of Quality of Life on Changes in Rents and Values

This section examines the relationship between quality of life in 2000 and the changes in rental prices and home values between 2000 and 2007. That home values increased during this period both absolutely and relative to rents has been widely documented. The first two columns of Table 6 regress the changes in log rent and log value fixed effects on the rent-based quality of life index for 2000. The results show that both rents and values increased disproportionately in high quality of life areas with statistically significant coefficients of 0.155 and 0.867. The magnitudes are much larger for values than rents. Based on the summary statistics reported in Table 3, moving from the 10^{th} percentile to the 90^{th} percentile of rent-based quality of life (an increase of 0.188) is associated with a 0.163 increase in log home values but only a 0.029 increase in log rents. These results suggest that the demand for housing in high quality of life areas increased considerably between 2000 and 2007. However, the much greater increase in values than rents suggests that market participants expected the demand for living in high quality of life areas to continue to grow.

A complementary approach is to look at housing value-rent ratios (aka price-rent ratio or inversely rent-price ratio) and examine how these relate to quality of life across areas. A higher value-rent ratio indicates that the demand for housing in the area is expected to grow faster than other areas (Campbell et al. 2009). Higher future demand for local housing does not affect current rental payments because these reflect the present user cost of housing, but higher future demand does increase current housing values. The third and fourth columns of Table 6 regress the log value-rent ratios in 2000 and 2007 on the rent-based quality of life estimate for 2000. The results in both columns suggest that a higher quality of life increases the value-rent ratio in an area with coefficients of 0.432 and 1.144 in 2000 and 2007, respectively.[22] These results suggest that the demand for housing was expected to increase in high quality of life areas in both years, but by 2007 the expected growth in demand had grown quite considerably as values grew much more quickly than rents. As economists and the general public were soon reminded, however, expectations are not always accurate and asset values based on them can often become considerably distorted. Hence, quality of life rankings should use housing rents and not housing values.

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, owner-occupied housing values, or some combination of the two. On theoretical grounds, rents are the superior measure of housing prices because rents

[22] Lee and You (2011) also document that the value-income ratio is higher in high quality of life areas but they do not focus on changes over time.

reflect the current user cost of housing, but housing values are based on the net present value of future rental income and do not necessarily reflect the present user cost of housing. However, many researchers have used a combination of rents and values assuming that the two basically measure the same thing.

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. Expected and actual growth in rental payments differs across areas causing housing values to be more dispersed than rents across areas. 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 WP 14472

Albouy D (2009) The unequal geographic burden of federal taxation. J Polit Econ 117(4):635-667

Banzhaf HS, Farooque O (2012) Interjurisdictional housing prices and spatial amenities: which measures of housing prices reflect local public goods? NBER WP 17809

Beeson PE, Eberts, RW (1989) Identifying productivity and amenity effects in interurban wage differentials. Rev Econ Stat 71(3):443-452

Blomquist GC, Berger MC, Hoehn, JP (1988) New estimates of quality of life in urban areas. Amer Econ Rev 78(1):89–107

Campbell SD, Davis MA, Gallin J, Martin RF (2011) What moves housing markets: a variance decomposition of the rent–price ratio. J Urban Econ 66(2):90-102

Chen Y, Rosenthal SS (2008) Local amenities and life-cycle migration: Do people move for jobs or fun? J Urban Econ, 64(3):519-537

Clark TE (1995) Rents and prices of housing across areas of the United States: a cross-section examination of the present value model. Reg Sci Urban Econ 25(2):237-247

Davis MA, Lehnert A, Martin RF (2008) The rent-price ratio for the aggregate stock of owner-occupied housing. Rev Income Wealth 54(2):279-284

Davis MA, Ortalo-Magné F (2011) Household expenditures, wages, rents. Rev Econ Dyn14(2):248–261

DuMond JM, Hirsch BT, Macpherson DA (1999) Wage differentials across labor markets and workers: does cost of living matter? Econ Inq 37(4):577-598

Gabriel SA, Mattey JP, Wascher WL (2003) Compensating differentials and evolution in the quality of life among U.S. states. Reg Sci Urban Econ 33(5):619-649

Gabriel SA, Rosenthal SS (2004) Quality of the business environment versus quality of life: do firms and households like the same cities? Rev Econ Stat 86(1):438–444

Garner TI, Verbrugge R (2009) Reconciling user costs and rental equivalence: evidence from the US consumer expenditure survey. J Hous Econ 18(3):172-192

Glaeser EL, Gyourko J, Saiz A (2008) Housing supply and housing bubbles. J Urban Econ 64(2):198-217

Greenwood MJ, Hunt G, Rickman DS, Treyz GI (2001) Migration, regional equilibrium, and the estimation of compensating differentials. Amer Econ Rev 81(5):1382-1390

Gyourko J, Kahn M, Tracy J (1999) Quality of life and environmental comparisons. In: Cheshire P, Mills ES (eds) Handbook of regional and urban economics, vol. 3. North Holland, Amsterdam, pp 1413-1454

Gyourko J, Tracy J (1991) The structure of local public finance and the quality of life. J Polit Econ 99(4):774–806

Henderson JV (1982) Evaluating consumer amenities and interregional welfare differences. J Urban Econ 11(1):32-59

Howie P, Murphy SM, Wicks J (2010) An application of a stated preference method to value urban amenities. Urban Stud 47(2):235-256

Kahn ME (1995) A revealed preference approach to ranking city quality of life. J Urban Econ 38(2):221-235

Koo J, Phillips KR, Sigalla FD (2000) Measuring regional cost of living. J Bus Econ Stat 18(1):127-136

Krupka DJ, Donaldson K (2007) Wages, rents and heterogeneous moving costs. IZA DP 3224

Lee S, You SD (2011) The price-to-income ratio and the quality of life. University of British Columbia Working Paper

Ogaki M, Reinhart CM (1998) Measuring intertemporal substitution: the role of durable goods. J Polit Econ 106(5):1078–1098

Oswald AJ, Wu S (2010) Objective confirmation of subjective measures of human well-being: evidence from the USA. Sci 327 (2010):576–579

Oswald AJ, Wu S (2011) Well-being across America. Rev Econ Stat 93(4):1118–1134

Partridge MD, Rickman DS, Olfert MR, Ali K (2012) Dwindling U.S. internal migration: evidence of spatial equilibrium or structural shifts in local labor markets? Reg Sci Urban Econ 42(1-2):375–388

Piazessi M, Schneider M, Tuzel S (2007) Housing, consumption, and asset pricing. J Financ Econ 83(3):531-569

Rappaport J (2007) Moving to nice weather. Reg Sci Urban Econ 37(3):375–398

Rappaport J (2009) The increasing importance of quality of life. J Econ Geogr 9(6):779-804

Roback J (1982) Wages, rents, and the quality of life. J Polit Econ 90(6):1257-1278

Rosen S (1979) Wage-based indexes of urban quality of life. In: Mieskowski P, Straszheim M (eds) Current issues in urban economics. Johns Hopkins University Press, Baltimore, pp 74-104

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

Shapiro JM (2006) Smart cities: quality of life, productivity, and the growth effects of human capital. Rev Econ Stat 88(2):324-335

Stover ME, Leven CL (1992) Methodological issues in the determination of the quality of life in urban areas. Urban Stud 29(5):737-754

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

Winters JV (2009) Wages and Prices: are workers fully compensated for cost of living differences? Reg Sci Urban Econ 39(5):632-643

Winters JV (2011a) Human capital, higher education institutions, and quality of life. Reg Sci Urban Econ 41(5):446-454

Winters JV (2011b) Why are smart cities growing? Who moves and who stays. J Reg Sci 51(2):253-270

Table 1: Summary Statistics for QOL Estimates, 2007

	Rent-based QOL Estimate	Value-based QOL Estimate
Mean	0.005	0.001
Standard Deviation	0.058	0.093
Max - Min	0.435	0.604
90th - 10th percentile	0.143	0.225
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	0.266	1	0.402	1
Medford, OR CBSA*	0.162	2	0.311	3
Santa Barbara-Santa Maria-Goleta, CA CBSA*	0.156	3	0.323	2
Burlington-South Burlington, VT CBSA	0.154	4	0.173	15
State College, PA CBSA*	0.143	5	0.126	31
Fort Walton Beach-Crestview-Destin, FL CBSA*	0.129	6	0.116	33
Chico, CA CBSA*	0.124	7	0.248	7
Morgantown, WV CBSA	0.111	8	0.066	62
Bangor, ME CBSA	0.110	9	0.098	38
Eugene-Springfield, OR CBSA	0.108	10	0.164	18
San Luis Obispo-Paso Robles, CA CBSA*	0.106	11	0.303	4
Blacksburg-Christiansburg-Radford, VA CBSA*	0.104	12	0.059	65
Coeur d'Alene, ID CBSA*	0.102	13	0.209	11
Anchorage, AK CBSA	0.098	14	0.093	45
St. George, UT CBSA	0.094	15	0.094	43
Bowling Green, KY CBSA	0.092	16	0.024	94
Panama City-Lynn Haven, FL CBSA*	0.091	17	0.088	48
Missoula, MT CBSA	0.089	18	0.154	20
New Orleans-Metairie-Bogalusa, LA CSA	0.089	19	-0.020	155
Portland-Vancouver-Beaverton, OR-WA CBSA	0.088	20	0.157	19

*Indicates 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	-0.027	-0.029
Standard Deviation	0.071	0.080
Max - Min	0.429	0.485
90th - 10th percentile	0.188	0.208
75th - 25th percentile	0.093	0.098

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
Prescott, AZ CBSA	0.196	1	0.246	1
Missoula, MT CBSA	0.195	2	0.217	2
St. George, UT CBSA	0.157	3	0.159	7
Billings, MT CBSA*	0.131	4	0.140	13
Cheyenne, WY CBSA	0.127	5	0.105	23
Fort Walton Beach-Crestview-Destin, FL CBSA*	0.116	6	0.068	33
Flagstaff, AZ CBSA	0.105	7	0.098	27
Eugene-Springfield, OR CBSA	0.103	8	0.145	10
Great Falls, MT CBSA*	0.102	9	0.141	12
Coeur d'Alene, ID CBSA*	0.100	10	0.136	14
Grand Junction, CO CBSA	0.099	11	0.121	17
Morgantown, WV CBSA	0.089	12	0.009	82
Albany-Corvallis-Lebanon, OR CSA*	0.089	13	0.129	15
Panama City-Lynn Haven, FL CBSA*	0.089	14	0.061	36
Lake Havasu City-Kingman, AZ CBSA	0.086	15	0.102	24
Medford, OR CBSA*	0.084	16	0.153	9
Casper, WY CBSA*	0.084	17	0.101	25
Chico, CA CBSA*	0.083	18	0.116	19
Abilene, TX CBSA	0.082	19	0.025	67
Lewiston, ID-WA CBSA*	0.080	20	0.106	22

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

Table 5: Comparison of Year 2000 QOL Ranks for 20 Largest Metro Areas

CBSA/CSA Name	Rent-based QOL Rank (out of 293)	Value-based QOL Rank (out of 293)	Chen-Rosenthal QOL Rank (out of 346)	Albouy QOL Rank (out of 241)
New York-Newark-Bridgeport, NY-NJ-CT-PA	173	41	203	43
Los Angeles-Long Beach-Riverside, CA	129	42	20	17
Chicago-Naperville-Michigan City, IL-IN-WI	267	229	274	80
Washington-Baltimore-N. VA, DC-MD-VA-WV	228	258	316	116
Boston-Worcester-Manchester, MA-RI-NH	227	81	91	34
San Jose-San Francisco-Oakland, CA	86	6	3	6
Philadelphia-Camden-Vineland, PA-NJ-DE-MD	275	275	340	184
Dallas-Fort Worth, TX	247	285	323	176
Detroit-Warren-Flint, MI	291	289	342	186
Miami-Fort Lauderdale-Pompano Beach, FL	123	187	75	33
Houston-Baytown-Huntsville, TX	280	292	335	221
Atlanta-Sandy Springs-Gainesville, GA-AL	219	280	295	175
Seattle-Tacoma-Olympia, WA	138	74	68	30
Minneapolis-St. Paul-St. Cloud, MN-WI	215	237	313	143
Phoenix-Mesa-Scottsdale, AZ	131	201	205	62
Cleveland-Akron-Elyria, OH	230	160	288	126
San Diego-Carlsbad-San Marcos, CA	22	11	12	7
St. Louis-St. Charles-Farmington, MO-IL	272	279	307	170
Denver-Aurora-Boulder, CO	140	140	127	35
Pittsburgh-New Castle, PA	154	109	287	188

Table 6: Effects of Rent-based QOL on Changes in Log Rents and Home Values, 2000-2007

Dependent Variable	Δ Ln Rent FE, 2000-2007	Δ Ln Value FE, 2000-2007	Ln Value-Rent Ratio, 2000	Ln Value-Rent Ratio, 2007
Rent-based QOL	0.155***	0.867***	0.432***	1.144***
	(0.056)	(0.143)	(0.132)	(0.217)
R^2	0.03	0.11	0.04	0.09

Standard errors in parentheses. ***Significant at 1%.

Appendix Table A: Complete Quality of Life Estimates and Rankings, 2000 & 2007

CBSA/CSA Name	Rent-based Est. 2007	Rent-based Rank 2007	Value-based Est. 2007	Value-based Rank 2007	Rent-based Est. 2000	Rent-based Rank 2000	Value-based Est. 2000	Value-based Rank 2000
Abilene, TX CBSA	0.058	48	-0.054	209	0.082	19	0.025	67
Albany, GA CBSA	-0.013	175	-0.046	200	-0.104	255	-0.115	261
Albany-Corvallis-Lebanon, OR CSA*	0.058	50	0.146	21	0.089	13	0.129	15
Albany-Schenectady-Amsterdam, NY CSA	-0.034	216	-0.033	174	-0.120	265	-0.097	242
Albuquerque, NM CBSA	0.007	136	-0.009	140	0.011	91	0.009	83
Alexandria, LA CBSA*	0.056	53	-0.032	172	0.015	83	-0.013	110
Allentown-Bethlehem-Easton, PA-NJ CBSA*	-0.015	178	0.023	96	-0.111	259	-0.077	213
Altoona, PA CBSA*	0.041	78	-0.005	133	-0.071	211	-0.056	181
Amarillo, TX CBSA	-0.003	160	-0.067	226	-0.011	117	-0.048	167
Ames-Boone, IA CSA	0.028	100	0.014	104	-0.020	132	-0.036	139
Anchorage, AK CBSA	0.098	14	0.093	45	-0.001	105	-0.043	158
Anniston-Oxford, AL CBSA	0.051	58	-0.009	138	0.002	98	-0.016	115
Appleton-Oshkosh-Neenah, WI CSA*	-0.099	286	-0.060	219	-0.132	273	-0.096	241
Asheville-Brevard, NC CSA	0.049	63	0.075	57	0.058	42	0.085	31
Athens-Clarke County, GA CBSA*	0.034	88	0.012	107	-0.010	116	-0.021	120
Atlanta-Sandy Springs-Gainesville, GA-AL CSA	-0.026	206	-0.101	267	-0.074	219	-0.148	280
Atlantic City-Hammonton, NJ CBSA*	-0.053	250	0.031	81	-0.232	293	-0.197	290
Augusta-Richmond County, GA-SC CBSA	-0.048	241	-0.086	251	-0.062	194	-0.072	206
Austin-Round Rock, TX CBSA	-0.016	185	-0.066	224	-0.028	145	-0.089	231
Bakersfield, CA CBSA	-0.023	201	0.044	73	-0.063	200	-0.055	179
Bangor, ME CBSA	0.110	9	0.098	38	0.055	43	0.059	38
Barnstable Town, MA CBSA*	0.038	81	0.185	13	-0.005	111	0.113	20
Baton Rouge-Pierre Part, LA CSA	-0.011	172	-0.080	243	-0.051	179	-0.074	208
Battle Creek, MI CBSA*	0.004	146	-0.040	188	-0.116	261	-0.140	274
Beaumont-Port Arthur, TX CBSA	-0.097	284	-0.186	292	-0.133	274	-0.183	288
Bellingham, WA CBSA	0.028	104	0.142	22	0.070	30	0.107	21
Bend-Prineville, OR CSA*	0.059	46	0.243	8	0.061	35	0.121	18
Billings, MT CBSA*	0.031	94	0.020	99	0.131	4	0.140	13
Binghamton, NY CBSA*	-0.016	184	-0.055	212	-0.040	161	-0.029	131
Birmingham-Hoover-Cullman, AL CSA	-0.017	188	-0.080	244	-0.089	242	-0.118	263
Bismarck, ND CBSA*	0.009	131	-0.043	196	0.061	36	0.045	45
Blacksburg-Christiansburg-Radford, VA CBSA*	0.104	12	0.059	65	0.017	76	-0.005	96
Bloomington, IN CBSA	0.051	57	-0.021	156	0.028	65	-0.003	95
Bloomington-Normal, IL CBSA	-0.043	232	-0.078	241	-0.099	249	-0.103	249
Boise City-Nampa, ID CBSA*	0.022	115	0.043	74	0.000	101	-0.027	127
Boston-Worcester-Manchester, MA-RI-NH CSA	0.022	113	0.130	27	-0.078	227	0.011	81
Bowling Green, KY CBSA	0.092	16	0.024	94	0.028	66	-0.007	103
Brownsville-Harlingen-Raymondville, TX CSA	-0.089	281	-0.111	273	-0.028	144	-0.035	137
Brunswick, GA CBSA*	0.014	125	0.047	72	-0.062	196	-0.050	171
Buffalo-Niagara-Cattaraugus, NY CSA	-0.061	257	-0.071	233	-0.118	264	-0.091	233
Burlington-South Burlington, VT CBSA	0.154	4	0.173	15	0.070	28	0.092	29
Canton-Massillon, OH CBSA*	-0.053	251	-0.039	185	-0.064	202	-0.040	149
Cape Coral-Fort Myers, FL CBSA	0.002	148	0.030	82	0.008	92	0.001	90
Casper, WY CBSA*	-0.039	226	-0.045	197	0.084	17	0.101	25
Cedar Rapids, IA CBSA	-0.012	174	-0.028	163	-0.084	235	-0.067	197
Champaign-Urbana, IL CBSA	0.015	123	-0.025	160	-0.027	143	-0.063	191
Charleston, WV CBSA	-0.023	200	-0.067	229	-0.075	222	-0.081	223
Charleston-North Charleston-Summerv., SC CBSA	0.069	38	0.041	75	0.018	73	-0.008	105

Charlotte-Gastonia-Salisbury, NC-SC CSA	-0.048	238	-0.092	259	-0.062	197	-0.085	225
Charlottesville, VA CBSA	0.075	34	0.096	40	0.035	57	0.006	87
Chattanooga-Cleveland-Athens, TN-GA CSA	-0.036	221	-0.047	202	-0.033	151	-0.039	147
Cheyenne, WY CBSA	0.022	114	0.007	115	0.127	5	0.105	23
Chicago-Naperville-Michigan City, IL-IN-WI CSA	-0.062	259	-0.038	182	-0.126	267	-0.086	229
Chico, CA CBSA*	0.124	7	0.248	7	0.083	18	0.116	19
Cincinnati-Middletown-Wilm., OH-KY-IN CSA	-0.108	287	-0.128	281	-0.144	284	-0.129	271
Clarksville, TN-KY CBSA*	0.051	59	0.006	118	0.012	89	-0.023	124
Cleveland-Akron-Elyria, OH CSA	-0.040	229	-0.049	205	-0.082	230	-0.045	160
Coeur d'Alene, ID CBSA*	0.102	13	0.209	11	0.100	10	0.136	14
College Station-Bryan, TX CBSA*	0.028	102	-0.028	162	-0.016	125	-0.081	221
Colorado Springs, CO CBSA	0.058	47	-0.005	134	0.049	50	-0.020	119
Columbia, MO CBSA	0.028	101	-0.032	170	0.067	32	0.031	61
Columbia-Newberry, SC CSA	-0.032	214	-0.098	262	-0.071	209	-0.095	238
Columbus-Auburn-Opelika, GA-AL CSA	0.053	56	-0.012	145	0.000	102	-0.037	143
Columbus-Marion-Chillicothe, OH CSA	-0.063	261	-0.089	255	-0.126	266	-0.114	260
Corpus Christi-Kingsville, TX CSA	-0.018	189	-0.113	275	-0.060	192	-0.108	256
Cumberland, MD-WV CBSA*	-0.038	224	0.003	121	-0.018	128	0.026	66
Dallas-Fort Worth, TX CSA	-0.071	271	-0.148	287	-0.096	247	-0.166	285
Dalton, GA CBSA*	0.011	129	-0.012	144	-0.016	124	-0.035	138
Danville, IL CBSA	-0.068	266	-0.091	256	-0.050	177	-0.050	170
Danville, VA CBSA*	-0.003	157	-0.082	247	-0.022	139	-0.021	122
Davenport-Moline-Rock Island, IA-IL CBSA	-0.025	204	-0.030	168	-0.058	189	-0.051	172
Dayton-Springfield-Greenville, OH CSA	-0.040	228	-0.065	223	-0.117	262	-0.106	253
Decatur, IL CBSA*	-0.089	282	-0.169	291	-0.138	277	-0.145	277
Denver-Aurora-Boulder, CO CSA	-0.015	182	-0.019	151	-0.022	140	-0.036	140
Des Moines-Newton-Pella, IA CSA	-0.068	268	-0.110	272	-0.056	188	-0.085	227
Detroit-Warren-Flint, MI CSA	-0.121	290	-0.132	282	-0.217	291	-0.192	289
Dothan-Enterprise-Ozark, AL CSA	0.045	70	-0.002	128	-0.009	114	-0.024	125
Dover, DE CBSA	0.008	135	-0.059	216	-0.022	137	-0.042	155
Dubuque, IA CBSA	0.036	84	0.029	83	-0.021	135	0.003	89
Duluth, MN-WI CBSA*	0.000	152	0.026	89	-0.090	244	-0.067	195
Eau Claire-Menomonie, WI CSA	0.023	112	0.000	125	-0.034	153	-0.006	99
El Centro, CA CBSA*	-0.125	292	0.023	95	-0.069	207	-0.059	185
El Paso, TX CBSA	-0.009	166	-0.017	148	-0.049	174	-0.060	186
Elmira, NY CBSA*	0.044	74	-0.029	166	-0.037	156	-0.059	184
Erie, PA CBSA	-0.039	227	-0.031	169	-0.075	223	-0.038	146
Eugene-Springfield, OR CBSA	0.108	10	0.164	18	0.103	8	0.145	10
Evansville, IN-KY CBSA	0.007	138	-0.054	210	-0.077	226	-0.091	232
Fairbanks, AK CBSA	0.086	25	0.094	42	0.060	39	0.065	35
Fargo-Wahpeton, ND-MN CSA	0.012	128	-0.003	132	-0.003	107	-0.014	112
Farmington, NM CBSA	0.005	141	0.081	53	0.014	85	0.026	63
Fayetteville, NC CBSA	0.076	31	0.010	113	0.071	26	0.045	44
Fayetteville-Springdale-Rogers, AR-MO CBSA	0.030	95	0.010	112	-0.020	133	-0.041	152
Flagstaff, AZ CBSA	0.029	97	0.083	51	0.105	7	0.098	27
Florence, SC CBSA*	-0.009	168	-0.041	190	-0.095	246	-0.079	216
Florence-Muscle Shoals, AL CBSA	-0.007	165	-0.070	232	-0.032	150	-0.036	142
Fond du Lac-Beaver Dam, WI CSA*	-0.049	243	-0.007	135	-0.089	243	-0.027	128
Fort Collins-Loveland, CO CBSA	0.065	43	0.088	47	0.044	51	0.041	50
Fort Smith, AR-OK CBSA	-0.003	158	-0.043	195	0.012	90	-0.007	101
Fort Walton Beach-Crestview-Destin, FL CBSA*	0.129	6	0.116	33	0.116	6	0.068	33
Fort Wayne-Huntington-Auburn, IN CSA	-0.087	279	-0.155	289	-0.130	271	-0.176	287
Fresno-Madera, CA CSA	-0.031	213	0.069	60	-0.029	147	-0.009	107
Gadsden, AL CBSA*	0.050	60	-0.009	137	-0.063	199	-0.062	189

Gainesville, FL CBSA	-0.048	242	-0.041	193	0.058	41	0.022	68
Goldsboro, NC CBSA*	-0.006	163	0.017	102	0.024	69	0.046	43
Grand Forks, ND-MN CBSA*	-0.023	199	-0.077	240	0.044	52	0.021	69
Grand Junction, CO CBSA	0.049	65	0.093	44	0.099	11	0.121	17
Grand Rapids-Muskegon-Holland, MI CSA	-0.027	209	-0.037	179	-0.100	250	-0.098	243
Great Falls, MT CBSA*	0.037	82	0.073	59	0.102	9	0.141	12
Green Bay, WI CBSA	-0.061	255	-0.041	192	-0.143	281	-0.105	252
Greensboro-Winston-Salem-High Point, NC CSA	-0.015	180	-0.050	207	-0.077	224	-0.075	210
Greenville, NC CBSA	-0.009	167	-0.040	189	-0.088	241	-0.069	198
Greenville-Spartanburg-Anderson, SC CSA	-0.014	176	-0.040	186	-0.084	234	-0.096	240
Gulfport-Biloxi-Pascagoula, MS CSA	0.050	62	-0.026	161	-0.002	106	-0.043	157
Hagerstown-Martinsburg, MD-WV CBSA*	-0.035	218	0.014	105	-0.084	232	-0.071	204
Hanford-Corcoran, CA CBSA*	0.066	42	0.134	24	-0.050	178	-0.071	202
Harrisburg-Carlisle-Lebanon, PA CSA*	-0.010	170	-0.010	141	-0.109	257	-0.102	248
Harrisonburg, VA CBSA	0.014	124	0.027	88	-0.012	119	0.016	77
Hartford-West Hartford-Willimantic, CT CSA	-0.049	244	0.008	114	-0.144	283	-0.079	217
Hattiesburg, MS CBSA	0.033	91	-0.034	176	0.051	49	0.017	75
Hickory-Lenoir-Morganton, NC CBSA	0.001	150	-0.002	129	-0.005	110	-0.006	100
Honolulu, HI CBSA	0.266	1	0.402	1	0.068	31	0.167	5
Hot Springs, AR CBSA	0.079	28	0.033	80	0.030	63	0.037	54
Houma-Bayou Cane-Thibodaux, LA CBSA*	-0.037	223	-0.069	230	-0.051	182	-0.078	214
Houston-Baytown-Huntsville, TX CSA	-0.116	289	-0.201	293	-0.143	280	-0.210	292
Huntington-Ashland, WV-KY-OH CBSA*	0.006	140	-0.045	198	-0.066	203	-0.081	222
Huntsville-Decatur, AL CSA	-0.019	195	-0.069	231	-0.077	225	-0.107	254
Idaho Falls-Blackfoot, ID CSA	0.028	103	0.006	119	0.059	40	0.059	37
Indianapolis-Anderson-Columbus, IN CSA	-0.069	269	-0.132	283	-0.103	254	-0.134	272
Iowa City, IA CBSA*	0.029	98	0.006	116	-0.004	109	-0.010	108
Ithaca-Cortland, NY CSA	0.075	32	0.024	92	0.036	56	-0.005	97
Jackson, MI CBSA*	-0.016	183	-0.009	139	-0.128	269	-0.109	257
Jackson-Humboldt, TN CSA	-0.049	245	-0.115	278	-0.060	191	-0.075	209
Jacksonville, FL CBSA	0.024	105	0.001	124	-0.017	126	-0.072	205
Jacksonville, NC CBSA*	0.079	29	0.026	90	0.076	21	0.036	55
Jackson-Yazoo City, MS CSA	-0.020	196	-0.102	268	-0.085	237	-0.143	276
Janesville, WI CBSA	0.014	126	0.011	110	-0.154	289	-0.119	265
Jefferson City, MO CBSA	-0.045	234	-0.064	222	0.007	94	0.009	85
Johnson City-Kingsport-Bristol, TN-VA CSA	-0.033	215	-0.038	183	-0.039	159	-0.028	129
Johnstown, PA CBSA	-0.044	233	-0.018	150	-0.086	239	-0.037	145
Jonesboro-Paragould, AR CSA	0.029	99	-0.024	158	-0.008	112	-0.035	136
Joplin, MO CBSA	0.029	96	-0.033	173	0.044	53	0.009	84
Kalamazoo-Portage, MI CBSA	-0.006	164	-0.028	165	-0.102	253	-0.093	236
Kansas City-Overland Park, MO-KS CSA	-0.038	225	-0.084	249	-0.075	221	-0.121	266
Kennewick-Pasco-Richland, WA CBSA	-0.093	283	-0.105	269	-0.099	248	-0.115	262
Killeen-Temple-Fort Hood, TX CBSA	0.004	145	-0.059	218	0.061	34	0.020	70
Knoxville-Sevierville-La Follette, TN CSA	-0.011	173	-0.032	171	-0.009	115	-0.001	93
Kokomo-Peru, IN CSA*	-0.168	293	-0.150	288	-0.223	292	-0.239	293
La Crosse, WI-MN CBSA*	0.023	109	0.027	86	-0.074	218	-0.013	111
Lafayette-Acadiana, LA CSA	0.034	89	-0.010	142	-0.015	122	-0.030	132
Lafayette-Frankfort, IN CSA	-0.003	159	-0.097	261	-0.054	185	-0.079	218
Lake Charles-Jennings, LA CSA	-0.047	236	-0.112	274	-0.082	231	-0.105	251
Lake Havasu City-Kingman, AZ CBSA	0.043	76	0.131	25	0.086	15	0.102	24
Lakeland-Winter Haven, FL CBSA*	0.020	117	-0.001	126	-0.003	108	-0.031	133
Lancaster, PA CBSA	0.002	147	-0.003	130	-0.049	175	-0.035	135
Lansing-East Lansing-Owosso, MI CSA*	-0.048	239	-0.081	246	-0.140	278	-0.161	284
Laredo, TX CBSA*	-0.018	192	-0.034	175	-0.046	168	-0.040	150

Las Cruces, NM CBSA	0.086	22	0.113	34	0.015	81	0.034	58
Las Vegas-Paradise-Pahrump, NV CSA	-0.098	285	-0.094	260	-0.085	236	-0.153	281
Lawrence, KS CBSA	0.058	49	0.028	85	0.035	58	0.001	91
Lawton, OK CBSA	0.057	51	-0.017	147	0.074	23	0.029	62
Lewiston, ID-WA CBSA*	0.063	45	0.084	50	0.080	20	0.106	22
Lexington--Frankfort--Richmond, KY CSA	0.023	108	0.006	117	-0.031	148	-0.053	174
Lima-Van Wert-Wapakoneta, OH CSA	0.007	139	-0.002	127	-0.113	260	-0.108	255
Lincoln, NE CBSA*	0.004	144	-0.020	154	-0.009	113	-0.015	114
Little Rock-N. Little Rock-Pine Bluff, AR CSA	0.031	92	-0.018	149	-0.033	152	-0.055	178
Logan, UT-ID CBSA*	0.066	41	0.012	108	0.030	62	0.011	80
Longview, WA CBSA*	0.047	68	0.173	16	-0.055	186	0.031	60
Longview-Marshall, TX CSA*	0.001	149	-0.035	178	-0.037	157	-0.064	192
Los Angeles-Long Beach-Riverside, CA CSA	0.056	52	0.213	10	-0.018	129	0.047	42
Louisville-Elizabethtown-Scotts., KY-IN CSA	-0.018	190	-0.025	159	-0.071	210	-0.066	193
Lubbock-Levelland, TX CSA	0.036	85	-0.049	206	0.015	82	-0.056	180
Lynchburg, VA CBSA*	0.017	121	0.016	103	-0.042	164	-0.047	162
Macon-Warner Robins-Fort Valley, GA CSA*	-0.042	231	-0.114	277	-0.086	240	-0.110	259
Madison-Baraboo, WI CSA*	0.008	133	0.027	87	-0.051	180	-0.020	118
Mansfield-Bucyrus, OH CSA	-0.035	217	-0.039	184	-0.105	256	-0.067	196
McAllen-Edinburg-Mission, TX CBSA	-0.047	237	-0.098	263	-0.062	195	-0.058	182
Medford, OR CBSA*	0.162	2	0.311	3	0.084	16	0.153	9
Memphis, TN-MS-AR CBSA	-0.068	267	-0.146	286	-0.150	286	-0.202	291
Merced, CA CBSA*	-0.082	276	0.081	52	-0.071	213	-0.044	159
Miami-Ft. Lauderdale-Pomp. Beach, FL CBSA	0.069	37	0.095	41	-0.016	123	-0.060	187
Midland-Odessa, TX CSA	-0.064	263	-0.156	290	-0.018	130	-0.079	215
Milwaukee-Racine-Waukesha, WI CSA	-0.084	278	-0.046	199	-0.149	285	-0.102	247
Minneapolis-St. Paul-St. Cloud, MN-WI CSA	-0.015	181	-0.020	153	-0.073	215	-0.094	237
Missoula, MT CBSA	0.089	18	0.154	20	0.195	2	0.217	2
Mobile-Daphne-Fairhope, AL CSA	0.043	77	0.003	123	-0.042	165	-0.062	190
Modesto, CA CBSA*	-0.019	194	0.097	39	-0.071	212	-0.070	200
Monroe-Bastrop, LA CSA*	-0.064	262	-0.085	250	0.000	104	-0.023	123
Montgomery-Alexander City, AL CSA	0.023	110	-0.058	215	0.000	100	-0.050	168
Morgantown, WV CBSA	0.111	8	0.066	62	0.089	12	0.009	82
Muncie, IN CBSA*	-0.060	253	-0.100	266	-0.068	206	-0.085	228
Myrtle Beach-Conway-Georgetown, SC CSA	0.044	72	0.048	71	0.053	48	0.038	52
Naples-Marco Island, FL CBSA*	0.010	130	0.122	32	-0.032	149	0.000	92
Nashville--Murfreesboro--Columbia, TN CSA	0.009	132	-0.024	157	-0.080	229	-0.100	246
New Orleans-Metairie-Bogalusa, LA CSA	0.089	19	-0.020	155	-0.021	136	-0.036	141
New York-Newark-Bridge., NY-NJ-CT-PA CSA	0.018	120	0.136	23	-0.048	173	0.049	41
Niles-Benton Harbor, MI CBSA*	-0.005	162	0.035	77	-0.071	208	-0.048	166
Norwich-New London, CT CBSA	-0.061	256	0.010	111	-0.084	233	-0.033	134
Ocala, FL CBSA*	0.013	127	0.051	68	0.070	29	0.039	51
Ocean City, NJ CBSA*	-0.036	220	0.165	17	-0.101	252	-0.027	126
Oklahoma City-Shawnee, OK CSA	0.007	137	-0.057	214	0.003	96	-0.054	175
Omaha-Council Bluffs-Fremont, NE-IA CSA	-0.026	207	-0.062	220	-0.075	220	-0.099	245
Orlando-Deltona-Daytona Beach, FL CSA	0.087	21	0.069	61	0.001	99	-0.071	203
Owensboro, KY CBSA*	-0.124	291	-0.087	252	-0.047	171	-0.054	176
Palm Bay-Melbourne-Titusville, FL CBSA*	0.040	80	0.029	84	0.032	61	-0.021	121
Panama City-Lynn Haven, FL CBSA*	0.091	17	0.088	48	0.089	14	0.061	36
Parkersburg-Marietta-Vienna, WV-OH CBSA*	0.005	142	-0.040	187	-0.043	166	-0.043	156
Pensacola-Ferry Pass-Brent, FL CBSA*	0.086	24	0.033	79	0.072	24	0.032	59
Peoria-Canton, IL CSA	-0.046	235	-0.072	236	-0.154	287	-0.122	267
Philadelphia-Camden-Vine., PA-NJ-DE-MD CSA	-0.005	161	-0.003	131	-0.133	275	-0.140	275
Phoenix-Mesa-Scottsdale, AZ CBSA	-0.026	208	-0.019	152	-0.020	131	-0.070	201

Pittsburgh-New Castle, PA CSA	-0.037	222	-0.059	217	-0.035	154	-0.012	109
Pittsfield, MA CBSA	0.024	106	0.088	49	-0.028	146	0.057	39
Pocatello, ID CBSA*	0.031	93	-0.011	143	0.054	46	0.044	48
Port St. Lucie-Sebastian-Vero Beach, FL CSA	0.049	66	0.061	64	0.022	72	0.019	71
Portland-Lewiston-South Portland, ME CSA	0.071	36	0.130	26	0.054	47	0.122	16
Portland-Vancouver-Beaverton, OR-WA CBSA	0.088	20	0.157	19	0.002	97	0.037	53
Prescott, AZ CBSA	0.072	35	0.192	12	0.196	1	0.246	1
Provo-Orem, UT CBSA*	0.036	86	0.020	98	0.023	70	-0.006	98
Pueblo, CO CBSA	-0.051	247	-0.048	204	0.016	78	0.017	73
Raleigh-Durham-Cary, NC CSA	-0.025	205	-0.063	221	-0.061	193	-0.093	234
Rapid City, SD CBSA*	0.079	27	0.110	35	0.062	33	0.093	28
Redding, CA CBSA*	0.044	75	0.177	14	0.055	44	0.081	32
Reno-Sparks-Fernley, NV CSA	0.021	116	0.078	56	0.013	88	0.006	86
Richmond, VA CBSA	0.005	143	-0.008	136	-0.063	198	-0.081	220
Roanoke, VA CBSA	-0.051	248	-0.075	238	-0.046	167	-0.047	163
Rochester, MN CBSA	-0.030	211	-0.084	248	-0.110	258	-0.154	282
Rochester-Batavia-Seneca Falls, NY CSA	-0.024	202	-0.054	211	-0.067	204	-0.087	230
Rockford-Freeport-Rochelle, IL CSA	-0.064	264	-0.079	242	-0.165	290	-0.138	273
Rocky Mount, NC CBSA*	-0.084	277	-0.088	254	-0.046	169	-0.042	154
Rome, GA CBSA	-0.002	155	-0.038	181	-0.051	183	-0.051	173
Sacramento-Arcade-Yuba, CA-NV CSA	0.020	118	0.126	29	-0.012	120	0.015	78
Saginaw-Bay City-Saginaw Twp. N., MI CSA*	-0.049	246	-0.072	234	-0.154	288	-0.147	278
Salem, OR CBSA*	0.068	39	0.126	30	0.023	71	0.066	34
Salinas, CA CBSA*	0.075	33	0.268	6	0.018	75	0.169	3
Salisbury-Ocean Pines, MD CSA*	-0.076	274	-0.028	164	-0.036	155	-0.028	130
Salt Lake City-Ogden-Clearfield, UT CSA	0.048	67	0.022	97	0.008	93	-0.019	117
San Angelo, TX CBSA	0.035	87	-0.043	194	0.044	54	-0.007	104
San Antonio, TX CBSA	-0.010	171	-0.067	227	-0.063	201	-0.119	264
San Diego-Carlsbad-San Marcos, CA CBSA	0.086	23	0.237	9	0.075	22	0.142	11
San Jose-San Francisco-Oakland, CA CSA	0.067	40	0.273	5	0.014	86	0.160	6
San Luis Obispo-Paso Robles, CA CBSA*	0.106	11	0.303	4	0.055	45	0.157	8
Santa Barbara-Santa Maria-Goleta, CA CBSA*	0.156	3	0.323	2	0.072	25	0.169	4
Santa Fe-Espanola, NM CSA*	0.023	111	0.079	54	0.034	60	0.100	26
Sarasota-Bradenton-Punta Gorda, FL CSA	0.081	26	0.109	36	0.060	37	0.044	46
Savannah-Hinesville-Fort Stewart, GA CSA	-0.015	179	-0.041	191	-0.052	184	-0.069	199
Scranton--Wilkes-Barre, PA CBSA*	0.000	153	0.003	122	-0.073	216	-0.042	153
Seattle-Tacoma-Olympia, WA CSA	0.000	151	0.093	46	-0.022	138	0.017	74
Sheboygan, WI CBSA	0.024	107	0.057	66	-0.137	276	-0.076	212
Shreveport-Bossier City-Minden, LA CSA	-0.024	203	-0.081	245	-0.073	217	-0.128	270
Sioux City-Vermillion, IA-NE-SD CSA	-0.051	249	-0.092	258	-0.026	141	-0.048	165
Sioux Falls, SD CBSA*	0.040	79	0.013	106	0.015	80	0.004	88
South Bend-Elkhart-Mishawaka, IN-MI CSA	-0.080	275	-0.141	284	-0.129	270	-0.158	283
Spokane, WA CBSA	0.049	64	0.053	67	0.029	64	0.026	65
Springfield, IL CBSA	-0.060	254	-0.119	279	-0.118	263	-0.125	269
Springfield, MA CBSA*	-0.058	252	0.024	93	-0.039	160	0.044	47
Springfield, MO CBSA	0.050	61	0.019	100	0.040	55	0.016	76
St. George, UT CBSA	0.094	15	0.094	43	0.157	3	0.159	7
St. Joseph, MO-KS CBSA	-0.001	154	-0.047	201	-0.017	127	-0.050	169
St. Louis-St. Charles-Farmington, MO-IL CSA	-0.076	273	-0.107	271	-0.132	272	-0.147	279
State College, PA CBSA*	0.143	5	0.126	31	0.070	27	0.050	40
Stockton, CA CBSA*	-0.021	197	0.102	37	-0.101	251	-0.083	224
Sumter, SC CBSA	-0.061	258	-0.106	270	0.016	77	-0.007	102
Syracuse-Auburn, NY CSA	-0.019	193	-0.047	203	-0.094	245	-0.085	226
Tallahassee, FL CBSA*	0.056	54	0.036	76	0.060	38	0.036	56

Tampa-St. Petersburg-Clearwater, FL CBSA	0.033	90	0.018	101	0.014	87	-0.047	164
Terre Haute, IN CBSA	-0.070	270	-0.099	265	-0.038	158	-0.046	161
Texarkana, TX-Texarkana, AR CBSA*	-0.018	191	-0.072	235	-0.047	172	-0.079	219
Toledo-Fremont, OH CSA*	-0.113	288	-0.113	276	-0.126	268	-0.103	250
Topeka, KS CBSA	-0.030	212	-0.088	253	-0.041	163	-0.093	235
Tucson, AZ CBSA	0.054	55	0.078	55	0.024	68	0.041	49
Tulsa-Bartlesville, OK CSA	0.044	73	-0.013	146	0.014	84	-0.041	151
Tuscaloosa, AL CBSA	-0.021	198	-0.053	208	-0.015	121	-0.037	144
Tyler-Jacksonville, TX CSA	-0.010	169	-0.076	239	-0.046	170	-0.095	239
Utica-Rome, NY CBSA*	-0.029	210	-0.067	228	-0.073	214	-0.073	207
Valdosta, GA CBSA	0.018	119	-0.030	167	0.005	95	-0.008	106
Victoria, TX CBSA	-0.035	219	-0.092	257	-0.140	279	-0.176	286
Virg. Beach-Norfolk-Newp. News, VA-NC CBSA	0.017	122	0.012	109	0.000	103	-0.017	116
Visalia-Porterville, CA CBSA*	-0.041	230	0.050	69	-0.027	142	-0.001	94
Waco, TX CBSA	-0.063	260	-0.142	285	-0.041	162	-0.076	211
Washington-Balt.-N. VA, DC-MD-VA-WV CSA	-0.017	187	0.004	120	-0.078	228	-0.109	258
Waterloo-Cedar Falls, IA CBSA	0.046	69	0.025	91	0.018	74	0.026	64
Wausau-Merrill, WI CSA	-0.087	280	-0.074	237	-0.067	205	-0.061	188
Weirton-Steubenville, WV-OH CBSA*	-0.048	240	-0.035	177	-0.059	190	-0.058	183
Wenatchee, WA CBSA*	-0.014	177	0.129	28	0.035	59	0.089	30
Wheeling, WV-OH CBSA*	0.045	71	-0.038	180	-0.056	187	-0.054	177
Wichita Falls, TX CBSA*	0.008	134	-0.125	280	0.016	79	-0.040	148
Wichita-Winfield, KS CSA	-0.002	156	-0.057	213	-0.049	176	-0.098	244
Williamsport-Lock Haven, PA CSA*	0.064	44	0.049	70	-0.020	134	0.014	79
Wilmington, NC CBSA	0.037	83	0.064	63	0.024	67	0.034	57
Yakima, WA CBSA*	-0.016	186	0.034	78	-0.051	181	-0.014	113
York-Hanover-Gettysburg, PA CSA	-0.066	265	-0.067	225	-0.085	238	-0.067	194
Youngstown-Warren-East Liverpool, OH-PA CSA	-0.073	272	-0.099	264	-0.144	282	-0.125	268
Yuma, AZ CBSA	0.078	30	0.073	58	-0.012	118	0.019	72

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