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DANIEL A. BROXTERMAN^{*}, AND ANTHONY M. YEZER⁺

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ABSTRACT. The skill intensity ratio (SIR) varies across cities. This variation education has implications for economic research. Black, Kolesnikova, and Taylor (2009) demonstrate that estimated returns to education vary with housing cost. However, if differences in the SIR are caused by variation in housing cost, the same mechanism may cause variation in unobserved worker characteristics that contribute to productivity and higher wages. Theory and tests in this paper demonstrate a substantial effect of housing cost on the SIR implying that unobserved productivity is also associated with housing cost.

JEL Classification: J24, J31,

Keywords: skill intensity, agglomeration, returns to education, unobserved heterogeneity

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I. INTRODUCTION

The skill intensity ratio (SIR) is conventionally measured as the ratio of college educated to those lacking a college degree in either the adult population or among employed adults. This ratio varies substantially by city. In 2000, the SIR for Danville, VA was 0.13 while that for Stamford, CT, was 0.98. Rates of change in the SIR are similarly uneven. Between 1970 and 2000, the SIR of Danville doubled while that for Stamford nearly tripled. These statistics are not exceptional. The coefficient of variation of the SIR in the panel of 331 MSAs used in this study has been remarkably stable over time, ranging from 0.42 to 0.45 over the four censuses from 1970 to 2000. Thus, the SIR of cities has not converged over this substantial period. Given the forces that might be expected to promote convergence, it appears that countervailing factors have maintained differences in the SIR.

Differences in years of education are readily observed and can be used to adjust wages in economic analysis of labor market data from a cross section of cities. However, the fact that an observable like the SIR varies so dramatically across space suggests that other unobserved worker characteristics may also be unequally distributed. Glaeser, Ressenger, and Tobio (2008) state the issue clearly by differentiating between measured human capital and true human capital:

One potential concern with interpreting these results is that measured returns to human capital may not be measuring higher returns to human capital, but instead measuring high levels of true human capital associated with each coarse category of observed human capital. For example, if people with college degrees in some areas went to higher quality schools or have better work experience, then this would cause measured return to a college education to increase, even if the true returns to human capital were constant across space. We have no way of dealing with this hypothesis, and we will continue referring to the measured returns to human capital as returns to human capital, understanding that it may reflect other things. (p. 638)

If the variation of the SIR is due to factors unrelated to other worker characteristics, then it is possible that the heterogeneity in the SIR does not imply unobserved heterogeneity in the labor forces of cities. For example, it may be that education requirements vary across industries in a manner that is orthogonal to other dimensions of individual productivity. If this is true, then the spatial variation in the SIR might not have implications for other differences in productivity. Certainly differences in industrial structure contribute to spatial variation in the SIR. However, recent papers by Elvery (2010) and Hendricks (2011) find that industry mix accounts for only a modest fraction of differences in the SIR across cities.¹

The SIR tends to be positively associated with the cost of living in cities and negatively associated with the skill premium or the skilled wage ratio (SWR), measured as the ratio of skilled to unskilled worker wages. This variation has implications for the literature on labor markets. First it has implications for research on returns to education. Black, Kolesnikova, and Taylor (2009) demonstrate that the parameters of a Mincer wage equation vary across cities in a manner that can bias estimates of the returns to education. The problem arises because the SIR increases while the SWR falls with the cost of living. Accordingly, estimates of the nominal return to education using a national sample do not reflect real returns because the higher earnings of the more educated are due in part to their concentration in high cost cities. Meanwhile, returns to education estimated for individual cities find that the estimated return to education varies inversely with local house prices. Second, others have noted that earnings disparities are smaller in larger cities where the SIR is higher. This suggests a spatial mismatch for less skilled workers and leads to the possibility of reducing measured income inequality by relocating unskilled workers.

There are other possible causes of variation in the SIR across cities. Locational amenities that are differentially attractive to more educated workers could raise house prices, lower the SWR and raise the SIR. Differences in state and local taxes that drive a wedge between earnings and expenditure could have a role in explaining variation in both the SWR and SIR across areas. The nature and quality of local public services might be differentially attractive based on household education levels. Finally, size of the city itself could result in amenities that cause both productivity differentials and locational preferences that vary with education.

Testing for the effects of so many possible factors on the SIR is not feasible. The list of amenities is long and measurement error for some is likely to be large. Effects of differences in the progressivity of the tax system and quality of public services are difficult to model. The problem of determining who itemizes is particularly daunting given that this interacts with the real after tax cost of housing.

The empirical strategy adopted here is to test for determinants of changes in the SIR of cities. This allows the effects of most amenity, local public good, and tax considerations to be differenced out because they are relatively permanent features of cities. It provides an opportunity to determine the effects of variable factors such as city size, industrial mix, and

¹ For example, Hendricks (2011) estimates that only twenty percent of the variation in SIR across cities is due to cities with a more educated workforce specializing in more skill-intensive industries, while eighty percent is due to firms in high SIR cities generally producing with a higher proportion of educated workers.

house prices that have the ability to account for the failure of the SIR of cities to converge in recent years. Testing for factors that explain the change in SIR can identify sources of changes in unobserved heterogeneity which cannot be removed from data by differencing.²

The next section of this paper reviews recent research on variation in the SWR across cities. The third section analyzes the theoretical rational for believing that there is a relation between the cost of housing and both the SWR and SIR of cities. This is followed by a general stochastic specification of a model of the time series variation in SIR for a panel of cities. Empirical results in the fifth section indicate the dominant role of house price variation in explaining changes in the SIR of cities. Finally, the results of robustness tests are reported.

II. RESEARCH ON VARIATION IN THE SWR ACROSS CITIES

Any attempt to model variation in the SIR among cities must also consider the literature on differences in the SWR. Two approaches have been used to examine spatial variation in the SWR. First is the traditional Mincer equation in which wages or earnings are regressed on a vector of individual characteristics. This approach involves estimation in levels and requires inclusion of an exhaustive set of personal characteristics. There are questions of the appropriate functional form of the wage or earnings equation as well as the measurement of labor compensation. The results reported in the literature vary considerably. Even the relation between city size and SWR has been the object of controversy. Black, et al. (2009) find a negative relation between city size and the SWR, Moretti (2004) no relation, and Beeson (1991) and Gould (2007) report a positive effect of city size on the SWR. Furthermore, Moretti (2004) finds that the SIR of cities is negatively related to the SWR.³

There are a number of difficulties with using a Mincer equation to measure the SWR that could account for this lack of consensus regarding the relation between city size and the SWR. Most obvious is the assumption that a year of education or of employment experience has the same effect on worker productivity regardless of where the education or experience was received. It may well be that the average educational experience of a worker with a bachelor's degree differs systematically with city characteristics. This type of unobserved heterogeneity in worker skill or education could be an important factor influencing the estimates of these Mincer equations.

A second approach to empirical analysis of the SWR involves empirical tests relating differences in the earnings of the top and bottom quartiles to differences in city characteristics.

 $^{^{2}}$ If the differences between measured and true human capital among cities are constant, then simple differencing can remove their effects. However, if they are both varying and unobservable, the challenge to research is far greater.

³ For example, Moretti (2004) finds a systematic inverse relation between the SIR and SWR. A one percentage point rise in the supply of college graduates raises the wages of high school drop-outs by 1.9%, high school graduates by 1.6%, and college graduates by 0.4%.

This approach has produced unambiguous results. Wheeler (2004) finds that the relation between the SWR and city population is negative and significant. Kim, et al. (2009) reproduce this result. However, they argue that it is produced by omitted variable bias. When the change in housing price is added to an equation with the change in the SWR as the dependent variable, the effect of city size becomes non-significant, while house price change has a negative and significant effect. The estimated elasticity of SWR with respect to house price is consistent with expectations based on an income elasticity of demand for a primary residence of 0.3 found in the literature on housing demand.

There is a notable divergence between the difference in earnings estimates and the Mincer equations. In the difference estimates, the dependent variable is the ratio of earnings of the top quartile to the bottom quartile of households. This ratio is not based on education. Accordingly, there is a difference between the ideal test of the SWR and the tests actually performed in the literature relating changes in the earnings ratio to changes in house price.

III. RELATING HOUSING COST, SWR, AND SIR OF CITIES

Economic theory not only suggests the general relation among changes in house prices, SWR and SIR for cities, a calibrated model can place rather tight restrictions on the expected empirical relation among these variables. The theory is relatively straightforward.

Divide the labor force into two homogeneous groups: *skilled* workers with a bachelor's degree and *unskilled* workers with less education. The object of the modeling exercise is to determine the relative proportion of these two worker types, i.e. the SIR, in different cities. Workers are employed by perfectly competitive firms located in cities. The price of housing services varies significantly across locations because housing is not transportable and land costs vary significantly.⁴ Workers move freely among cities and between firms, taking prices and wages as given, and are subject to a no-arbitrage equilibrium in which their indirect utility is equated across cities.

Following the theoretical models in Black, et al. (2009) and Kim, et al. (2009), with two skill levels of labor and consequent differences in household income, the tradeoff between housing costs and wages or amenity will vary by worker type. Consider skilled workers, s, whose indirect utility in city i given by $V(y_{is}, p, r_i, q_i)$, where, y is earnings, p is the price of a composite commodity, r is a housing cost index, and q is the monetized price of a unit of amenity. In the conventional model, commodity prices are assumed constant while housing and amenity prices and earnings vary spatially. Totally differentiating indirect utility and applying

⁴ In addition to land costs, structure inputs could also influence differences in the supply price of housing. The consensus in the literature is that construction costs are relatively unimportant compared to land. Topography, number of individuals to be housed, land use regulation, and transportation systems determine the supply of urban land for housing. The relative importance of these factors varies among cities.

Roy's identity produces a familiar decomposition of the variation in compensation of skilled workers:

$$dy_{is} = h_{is} \, dr_i - a_i \, dq_i \tag{1}$$

where h_{is} and a_i are housing and amenity consumption respectively and dp is assumed equal to zero. If there is a second group of workers, noted u for unskilled, whose differential earnings across locations are represented by the counterpart of equation (1), the difference in earnings between skilled and unskilled workers in a given city is given by

$$(dy_{is} - dy_{iu}) = (h_{is} - h_{iu}) dr_i.$$
 (2)

The amenity effect is removed by differencing following the conventional assumption that amenities are pure local public goods. To the extent that amenity is not uniform within a city, the literature generally assumes that the differences are priced in the form of intra-area differences in taxes or housing cost. Finally, if intercity differences in differences in housing consumption between the two worker types are assumed to be a trivial second order effect, the differential in SWR across cities depends on $(h_s - h_u) dr_i$, i.e. it depends on the difference in housing consumption multiplied by differences in the price of housing services.

The assumption that the compensating variation in earnings across areas achieves a noarbitrage equilibrium of utility implies that the elasticity of the SWR with respect to housing cost, E_{SWR} , is given by

$$E_{SWR} = (\theta - 1) (\varepsilon - 1) H_u / \theta, \tag{3}$$

where θ is the SWR, ε is the income elasticity of demand for a primary residence, and H_u is expenditure on primary housing as a fraction of income for less-educated households.⁵

The elasticity of the SIR with respect to housing cost, E_{SIR} , is simply the product of this relative wage elasticity with the elasticity of substitution of college-educated for non-college-educated workers represented by σ^6 :

$$E_{SIR} = \sigma E_{SWR}.$$
 (4)

The parameters necessary to compute an estimate of the E_{SIR} are readily available. The value of 0.30 for ε was used in Kim, et al. (2009) and is comparable to estimates by Glaeser et al.

⁵ If household preferences are homothetic, $\varepsilon = 1$, and the return to education will be the same in all locations. This proposition is noted in Black, et al. (2009). The model setup here is similar to their work and indeed is standard in the literature. The major difference is that in this paper the SIR is endogenous, whereas elsewhere it is exogenous.

⁶ Here the elasticity of substitution of skilled for unskilled labor is defined as $d \ln(S/U) / d \ln(y_s/y_u)$ as opposed to the common definition based on the percentage change in input ratios due to a percentage change in the marginal rate of technical substitution.

(2008), and Ioannides and Zabel (2008). $H_u = 0.3$ reflects the approximate share spent on housing in the Consumer Expenditure Survey from the Bureau of Labor Statistics (Glaeser, 2008). The value of 2.0 for θ is obtained from the U.S. Census Bureau tabulation of households with at least a bachelor's degree versus those with less education.⁷ Finally, an extensive review of the literature by Hendricks (2011) led him to conclude that, while there was a modest range of estimates in empirical studies, the appropriate value for $\sigma = -1.6$.

Applying these parameters to the computations in (3) and (4) results in point estimates of $E_{SWR} = -0.105$ (or a 10% rise in housing cost produces a 1.05% fall in the SWR) and $E_{SIR} = 0.168$ (or a 10% rise in housing cost results in a 1.68% rise in the SIR). Given the substantial variation in housing cost with location shown in Table 1, this calibration makes clear the potential for variation in housing costs to produce sizeable variation in skill composition, i.e. in the SIRs, across cities. Indeed, the potential effect is so large and housing costs sufficiently volatile that it likely takes significant time for the labor force to adjust to changing housing costs. Similarly, variation in industry mix likely requires substantial time to have its full effect on the SIR of a city. Therefore, empirical tests performed here use changes over a decade, as has been the custom in most of the papers discussed in the review of previous research.

IV. VARIATION IN THE SIR AND CITY CHARACTERISTICS

It is useful to begin the process of stochastic specification with a general equation determining the number of skilled workers in the city as a function of population, industry mix, housing cost, and city and worker specific random effects:

$$\ln S_{it} = \alpha_s + \beta_s \ln N_{it} + \sigma_s M_{it} + \pi_s \ln R_{it} + \lambda_{is} + v_{st} + \varepsilon_{ist}, \qquad (5)$$

here S_{it} represents the number of skilled workers in city *i*, N_{it} is city population, M_{it} is a measure of industry mix, R_{it} is a housing cost index, λ_{is} is a skilled-worker specific city-error which includes amenity and tax effects, v_{st} is a skilled-worker specific time-error, and ε_{ist} is an observation specific error that includes time-varying, area-specific, skilled worker effects. An essentially identical equation can be written for the determinants of the log of unskilled workers, $\ln U_{it}$.

Differencing these two equations yields an expression for the logarithm of the SIR:

$$\ln S_{it} - \ln U_{it} = \alpha + \beta \ln N_{it} + \sigma \ln M_{it} + \pi \ln R_{it} + \lambda_i + \nu_t + \varepsilon_{it}.$$
(6)

In equation (6), the error terms lack *s* or *u* subscripts because they are difference terms, i.e. $\lambda_i = \lambda_{is} - \lambda_{iu}$, $v_t = v_{st} - v_{ut}$, and $\varepsilon_{it} = \varepsilon_{ist} - \varepsilon_{iut}$. Similarly $\alpha = \alpha_s - \alpha_u$, $\beta = \beta_s - \beta_u$, and $\pi = \pi_s - \pi_u$.

⁷ In Kim, et al. (2009), θ was set at 4.0 because it was the ratio of income of the top quartile to earnings of the bottom quartile. Here, the θ is half as large because it is the ratio of earnings of households with a bachelor's degree to earnings of households lacking a bachelor's degree.

Estimates of equation (6) usually with housing cost omitted but with other variables included, are common in the literature reviewed above. A positive relation between the SIR and city size is often reported. Industry mix effects are commonly observed. When housing cost is added, estimates of π are generally positive and significant but include omitted variable bias as housing prices are correlated with both amenity and tax differences included in λ_i .⁸ Fixed effects estimators can remove the influence of variation in λ_i that is permanent over the time period analyzed.

In spite of the differencing across worker types, estimating equation (6) without city fixed effects allows for the possibility of omitted variable bias. Specifically, urban amenities and tax differences will enter λ_i if they are valued differently by skilled and unskilled workers. By including fixed effects or differencing the variables over time, so that the equation relates changes in the SIR to changes in population, industry mix, and housing cost, the effects of most urban amenity, local public service quality, and tax variables, which change very slowly if at all over time, can be eliminated.⁹ An additional problem is measurement error in estimates of R_{it} that arises because of unobserved differences in housing quality across cities. Constant quality house price indexes for the cross section of U.S. MSAs used in this study are not available.

The elasticity of the SIR with respect to house price, E_{SIR} , in the theory section, can be estimated directly by differencing equation (6) over time. This has the added advantage of also differencing out the λ_i and removing the time invariant component of measurement errors in house price indexes. Specifically, the estimating equation for the differenced model is

$$\ln I_{it} - \ln I_{it-x} = \beta \left(\ln N_{it} - \ln N_{it-x} \right) + \sigma \left(\ln M_{it} - \ln M_{it-x} \right) + \pi \left(\ln R_{it} - \ln R_{it-x} \right) + \Delta v_t + \Delta \varepsilon_{it}$$
(7)

Here $\ln I_{it} = \ln S_{it} - \ln U_{it}$, and x = 10 based on availability of census data and following the general custom in the literature of examining decadal changes. In this case, the city error is differenced out and only the changes in the other two error terms remain.¹⁰ Accordingly, the possibility of omitted variable bias in the estimates of β , σ , and π is substantially reduced.

⁸ The models estimated in differences reported in this paper were also estimated in logarithms of levels in single cross sections and the resulting estimates of π are positive and significant but differ significantly from the fixed effect panel results reported in Table 2 due to the effects of omitted variable bias embodied in components of λ_i .

⁹ Glaeser (2008) has noted the potential role of differential evaluation of urban amenities in large cities in determining the relation between the SIR and population. Most urban amenity measures should be constant over the ten-year census interval used in this study. Similarly effects of progressivity in state and local taxes on the difference between gross and net of tax wage ratios should be relatively stable. Differencing over a decade allows for changes over longer periods of time and, in that sense, is even less likely to suffer from omitted variables bias.

¹⁰ The arguments here parallel those that Wheeler (2004) and Kim, et al. (2009) apply to the analysis of the SWR. These papers also set x = 10. The common source of measurement error is unobserved housing quality differences in each city. Indeed, the physical characteristics of housing vary significantly with the topography and climate of the city.

V. DATA AND ESTIMATION RESULTS

Following a general convention in the literature, the SIR is based on holding a bachelor's degree. Specifically, the SIR in a city is the number of college graduates (bachelor's degree or more) divided by the number of non-college graduates among the population of adults aged 25 years or older. Measures of city population, employment, and educational attainment come from tabulations of decennial census data in the U.S. Department of Housing and Urban Development's (HUD's) *State of the Cities Data Systems*. The definition of "city" varies between the metropolitan statistical area (MSA) and the core-based statistical area (CBSA) depending on which measure of housing cost is included among the independent variables in equations (6) and (7).¹¹

Finding a measure of housing cost appropriate for all households in a city is challenging. For low-income households, rental prices are an attractive choice. However, most households are owner-occupants. For these households the real after tax cost of housing is based on value and user cost that varies by income level. Use of house value is also complicated by the fact that it is based on expectations of future rents, and hence on the economic future of the city, whereas the theory developed here is based on the spot price of housing services.

In response to possible questions regarding the appropriate housing cost measure, results using three alternative housing cost indexes are presented. Two can potentially be used for cross-section comparisons while another, a repeat-sales index of changing house value, can only be used for differences over time. Both rental and owner price indexes are examined in an attempt to consider all possible alternatives.

The median owner's estimate of value and rent from the Census of Population and Housing is used in the tests for three reasons. First, it can be used in both level and change equations. Second, it is available for the 1970-1980 period as well as 1980-1990 and 1990-2000. Third, it covers the widest range of cities. While the quality of the median unit varies across cities, these differences persist given durability of the housing stock and hence much of the effect of variation in quality can be differenced away in the estimates of equation (7).

The Federal Housing Finance Agency's weighted repeat-sales housing price index for cities (FHFA HPI) is available for 130, 326, and 365 cities for the years 1980, 1990, and 2000 respectively. This means that differences over 1980-1990 are only available for 130 cities,

¹¹ An additional complication has to do with the geographic definitions of metropolitan areas. If definitions are not held constant over time, the same household could be observed in different cities across censuses periods without ever having moved. The HUD data take definitions from the 2000 census and apply them retroactively to metropolitan areas during the preceding years.

while 326 can be used for the 1990-2000 period. It may be that there are unobserved changes in unit quality that escape the index and that this source of error varies by city. Nevertheless, the FHFA HPI is widely used as a price index in panel studies of housing prices.

Descriptive statistics for the SIR, population, industrial composition, and three housing cost measures for different groups of cities over various time periods from 1970-2000 are displayed in levels in Table 1a, and in changes in Tables 1b, and 1c.¹² The mean SIR, population, and median home price have been rising over time. The rate of change in the SIR over the 1970-80 decade was notably faster than in more recent years but the coefficient of variation in the SIR and in median gross rent are both remarkably stable. Industrial composition indicates the steady rise in the share of professional services and falling manufacturing employment while the wholesale and retail trade share is virtually constant.¹³ Because the FHFA HPI is available only since 1980 and the sample of cities is smaller, separate tabulations of descriptive statistics are provided in Table 1c.

Estimates of equation (6) with fixed effects are presented in Table 2a for the sample of 331 MSAs across three intervals, 1970-80, 1980-90, and 1990-2000. The calibration based on theory suggests an E_{SIR} of 0.168. The estimates of π in models (2), (4), and (6) using median rent are highly significant but approximately twice the calibrated value while those based on median house values in models (1), (3), and (5) are equally significant and only slightly above 0.168. In contrast to expectations based on literature suggesting that SIR responds positively to city size, the estimated coefficient of population growth is negative. The negative estimates for coefficients of manufacturing and wholesale and retail trade and contrasting positive estimate for professional services are not surprising given differences in the skill intensity of these sectors.

Use of the FHFA repeat sale house price index reduces the panel of MSAs from 331 to 130 but the results for estimates of equation (6) in Table 2b are similar to those for median prices. The estimate of π is now very close to expectations based on the calibration. Population is never statistically significant and industry composition results are similar to those reported in Table 2a.

Estimates of the model in differences, i.e. equation (7), for the same group of 331 MSAs across the 1970-80, 1980-90, and 1990-2000 intervals, appear in Table 3a. The relation between changes in the logarithms of the SIR and median house value in columns (1), (3), and (5) are remarkably close to the expectation of 0.168. Effects of median rent are about twice as large. All house price results are significant at the one percent level. Population growth is negative

¹² The appendix contains a tabulation of the levels and changes in the SIR for the full set of MSAs used in this study. There are notable differences in both levels and rates of change. Smaller cities dominated by large institutions of higher education have the highest SIR levels.

¹³ The three employment shares – manufacturing, trade, and professional services – are the same ones used by Glaeser and Saiz (2004).

and significant while the industrial composition effects are similar to those in Table 2a. Comparable estimates using the logarithm of the change in the FHFA price index in Table 3b show house price effects that are virtually identical to those for median value and the agreement with theoretical expectations is even closer. Other effects are consistent except that the logarithm of population change is not statistically significant.

The relative importance of house price variation in determining changes in the SIR can be compared to the other variables considered here by examining Table 4. For each of the three housing cost variables, population, and the three industry mix variables, the estimated effect of both the mean absolute change and a one standard deviation in the change over a decade on the SIR is displayed. The mean change in the SIR over a decade is substantial. While some of the non-housing variables have significant elasticities with respect to the SIR, their variation over a decade is much smaller than that of house price. Because the overall importance for a variable in determining differential changes in SIR values across cities is the product of the elasticity estimate and the differences in rates of change across cities, the effects of house price changes, whether based on mean absolute change or standard deviation are much larger than other variables and comparable to the mean change in the SIR itself. Overall, in terms of explaining variation in the rate of change in the SIR across cities, the variation in housing cost over the typical decade between 1970 and 2000 has been far more important than the effects of changing population, or general changes in industrial structure. In answer to the question posed in the title of this paper, the role of housing cost in determining variation of the SIR is very large compared to other factors noted in the literature. Furthermore, the mechanism that relates house price variation to differences in the SIR should apply equally well to unobserved worker characteristics that, like education, are related to productivity.

VI. ROBUSTNESS CHECKS

This section reports the results of a series of robustness checks designed to determine if the relation between changing house prices and SIR can survive alternative specifications designed to test for possible statistical bias. The estimation results reported in the previous section are appropriate given the logical rational for equations (6) and (7) but the alternatives considered here are designed to respond to and hopefully anticipate any possible objections to that stochastic specification.

The first robustness test concerns the possibility that individuals are attracted to cities where workers with their level of education are concentrated. Berry and Glaeser (2005) and Glaeser (2008) have suggested that educated workers act as an amenity that is more valued by educated individuals. Alternatively, it may be that, as the fraction of more educated households rises, the character of local public goods production changes in a fashion that is differentially

attractive to more educated households.¹⁴ This possibility is tested in models (5) and (6) of Tables 2a and 3a by adding lagged SIR and/or the change in the logarithm of lagged SIR to the equations. Similarly, for estimates using repeat sales indexes in Tables 2b and 3b these lagged SIR terms are added to model (3). In all cases, the lagged SIR effects are positive indicating that there is persistence in rate of change in SIR and providing support for the observation in Berry and Gleaser (2005) and Glaeser (2008) that more educated workers appear to be attracted to areas with a higher SIR. However, the house price estimates in all these cases are robust or, if anything, are slightly larger and equally statistically significant in the models where lagged SIR or its lagged rate of change are added.

A second possible problem concerns the method used to measure the SIR of a city. Results reported in Tables 2 and 3 are based on the HUD dataset which tabulates the entire Census of Population and Housing. The disadvantage of using this 100% sample is that the available tabulations do not differentiate based on the employment and housing status of the population. All adults, regardless of their employment are included in the SIR measure. Similarly, there is no allowance for individuals who are not housed in units that are included in the price indexes.¹⁵ Individuals residing in farm housing, temporary housing, institutional units and group quarters are included in the estimates of the SIR. This introduces potential measurement error because the appropriate SIR for testing the theoretical model should be employed individuals living in permanent residential housing that is priced in the private market.

An alternative to the HUD data used for the robustness test is the Integrated Public Use Microdata Series (IPUMS) data (Ruggles, et al., 2010). This 5% sample is clearly less precise than the full census but it does allow selection of only employed adults aged over 24. The IPUMS data also permits exclusion of students, members of the military, and individuals living in temporary or institutional housing.¹⁶ Table 5a contains the results for equation (7) estimated using both HUD and IPUMS data. In all cases, the IPUMS estimate of π is slightly smaller but it is, if anything, closer to the calibrated value of 0.168 and its statistical significance is high. Overall, the results presented in Table 5a indicate that estimates using HUD and IPUMS data are very similar in spite of the variation in sample size and criteria for selection of individuals included in the SIR measurement.

¹⁴The specific example of local public schools seems an obvious possibility.

¹⁵ The effect of institutional and subsidized housing on housing cost is likely small compared to the question of whether value or rent should be used in the index. The results in Tables 2 and 3 show that there is a difference in the size but not the significance of the coefficient estimates between indexes based on value and rent.

¹⁶ In tabulating sample estimates from the IPUMS data, the analysis constructs MSAs with consistent geographic definitions by aggregating county groups and PUMAs using a procedure outlined by Jaeger et al. (1998) and updated by Beeson et al. (2010).

Another possible objection to the specification in equation (7) is that $\Delta \varepsilon_{it}$ is correlated with changing housing cost, or that changing the SIR of a city alters its housing cost. A search of the literature has uncovered no instance of a model in which the SIR or its rate of change has been used as a regressor in an equation with the rate of change in house prices as the dependent variable. There are instances of papers, stemming from Rauch (1993), that include average education as an argument of both city house price and wage equations. But this has been done as part of a Rosen-Roback model without theoretical justification. The recent Rosen-Roback literature, see Albouy (2008) for example, commonly includes education in the wage equation but it is not used to explain house prices. Given the accepted practice of excluding education from house price equations in the literature, its exclusion appears appropriate in equations such as (6) and particularly (7). It is difficult to imagine how a change in the SIR of a city, holding population constant, can cause house prices to change. Nevertheless, a robustness check for the endogeneity of house prices in equation (7) is included here.

As noted recently by Davidoff (2014), it is difficult to find instrumental variables for housing cost that satisfy an exclusion restriction on the SIR equation, vary over time and across cities, and are available for MSAs over several decades. Fortunately, Pennington-Cross (1997) developed the export price index (EPI) to serve as such an instrument. The EPI is designed to avoid problems of Bartik's (1991) employment share index.¹⁷ The EPI follows Brown, Coulson, and Engle (1992) in using location quotients to identify export industries in each city. Then relative export shares are used to weight national price change indexes to form a measure of price shocks experienced by individual cities. Recently Hollar (2011) has successfully applied the (EPI) to explain employment growth in both central cities and suburbs. One limitation of the EPI is that it does not include public employment. Accordingly, cities that are state capitals and the nation's capitol were omitted from the analysis.¹⁸ Table 5b allows easy comparison of OLS and IV estimates of equation (7) for the three house price indexes. The estimated coefficients of the housing cost change measures are numerically larger but have smaller *t*-ratios under IV.¹⁹

The three robustness tests performed here establish that the relation between housing cost changes and the SIR persists under substantial stressing. There is evidence that lagged SIR or its rate of change is important to current SIR or its rate of change but this has no effect on the estimated coefficients of other variables in equation (7). Substituting a more targeted measure of the SIR by using the five percent IPUMS sample for the HUD data had no significant effect on

¹⁷ Bartik (1991) takes national employment growth by sector and shares it out across cities in proportion to their shares of employment in that sector. This implicitly assumes that industrial growth in some cities does not come at the expense of growth in other locations.

¹⁸ Inclusion of the state capitols and Washington, DC has only a small effect on the size and significance of the estimated coefficients but the overall goodness of fit of the model, particularly the instruments, is lower.

¹⁹ The EPI panel used in the IV estimates is due to Larson (2010).

estimates. Finally, although house price equations in the literature do not include the SIR as an argument, IV estimates using the EPI as an instrument preserved the relation between housing cost and the SIR.

VII. CONCLUSIONS AND IMPLICATIONS

The model presented here explains the relation among the SIR, SWR, and housing cost in both levels and rates of change. In terms of levels, cities with high house prices have higher wages. They also have higher SIRs and lower SWRs. In terms of rates of change, cities with high rates of house price increase have faster rates of wage increase and rising SIR but falling SWR. The coefficient of variation of the SIR across the 331 MSAs considered here has been essentially constant across the 1970-2000 period. All of this is easily explained with a model of spatial equilibrium driven by the supply side of the labor market. The assumption, consistent with the empirical literature, that preferences for housing as a primary residence are non-homothetic, and that the income elasticity of demand for such a residence is significantly less than unity, play a major role in the argument. Indeed, the findings presented here may be interpreted as a demonstration that models based on the assumption that preferences are homothetic are problematic. Estimates of the empirical relation between changes in house price indexes and changes in the SIR are close to expectations based on a calibrated model. Finally, as shown in Table 1a, the coefficient of variation in median house value has been increasing over time providing a force that has tended to keep the SIR from converging across cities.

This view of inter-urban labor markets has a number of implications. For the literature that has used Mincer earnings or wage equations to attempt to determine the relation between the SWR and city size, the papers finding a negative relation consistent with that in the wage difference literature appear to be correct.

The findings reinforce the warning in Black, et al. (2009) that measures of the real returns from education using a national sample are overstated because the SIR rises with house price and this means that more-educated workers live in higher cost areas.²⁰ Their recommendation that estimates of returns to education be adjusted for differences in local housing cost is reinforced by the results reported here.

The nearly constant coefficient of variation observed for the SIR over 1970-2000 is consistent with the effects of changing house prices over this period. The elasticity of house price change in the panel of 331 cities used in this analysis with respect to initial 1970 price is 0.18. The faster rate of growth in house prices in cities where house prices were initially high provided a significant force preventing convergence of the SIR.

²⁰ The results are also consistent with their finding that returns to education estimated for individual cities vary inverse with local house prices.

Most important, the theory developed here, which predicts that observed differences in education are positively associated with house prices, also applies to other productivity differentials that result in higher earnings. Any of the sources of difference between measured human capital and true human capital noted in the introductory quotation by Glaeser, et al. (2008) could have been substituted for education in the theory section of this paper. The theory predicts that equally educated workers located in cities with different house prices should have different levels of productivity and earnings. Factors such as class rank, college quality, effort, etc., should be higher in the city with higher house prices. Such differences in unobservables are obviously a challenge to measure as Glaeser, et al. (2005) have noted. Recently, Johnson (2014) has explored the stylized fact that labor force participation of married women rises with house prices and Rosenthal and Strange (2008) have found that professionals work longer hours in cities with higher house prices in a fashion consistent with the model presented here.

This analysis calls into question the welfare implications of relocating low skill workers into cities with high house prices. Wages of low skill workers in cities with higher wages and house prices are relatively higher, i.e. the SWR is lower. This does not necessarily imply that selective migration out of low house price cities will raise the welfare of the unskilled. The falling SWR with city size is pecuniary rather than real as it results from the rise in house price with city size and the larger share of primary housing in the consumption bundle of low versus high income households. It is true that the unskilled worker wages grow faster after migrating to a high wage destination but this is easily explained by the job search model of migration.²¹

Rosen-Roback models assume that there is a stable tradeoff between wages and house prices. The model presented here suggests that this tradeoff depends on the skill level of the worker, i.e. it varies substantially within the population. Furthermore, rising house prices alter the relation between measured and true human capital so that even an analysis that compares wages of equally educated workers across cities with different house prices is problematic. The obvious resolution for this problem is to conduct Rosen-Roback research on cities with comparable house prices where differences are confined to the tradeoff between wages and amenity. The results of such studies should differ from those that include cities with very different house prices.

The findings suggest complications for research on agglomeration economies and human capital externalities in cities. Consider what happens in cities where house prices increase over a significant period of time because of population growth and inelastic supply. Such cities will have higher average wages and SIR. Furthermore, both wages and SIR in such cities will increase rapidly over time compared to other cities where supply is elastic and housing cost is

²¹ For a discussion of the job search model of migration, and the rational for different rates of appreciation of skilled and unskilled migrant wages at a destination, see Yezer and Thurston (1976).

stable. It is tempting to conclude that this correlation between rates of change of wages and the SIR means the collection of more-educated workers in a given city results in an acceleration of wages and productivity. The analysis here shows that all these effects happen naturally in an area that has rising housing prices and that the rise in the SIR with house prices also produces a rise in unobservable components of skill. Urban growth that may arise due to simple Thunen advantages based on nodality will also raise housing prices and produce a positive association between changes in wages and the SIR.²² Thus the association between rising SIR and wage growth may have nothing to do with agglomeration economies of any sort. Conversely, the fall in SIR with falling housing prices in declining cities is a natural process and need not reflect on the mechanism that generates or reinforces urban decline. Alternatively, this natural process that raises the SIR in growing cities with inelastic housing supply, and which lowers the SIR in declining cities where Glaeser and Gyourko (2005) have established supply is inelastic, may have everything to do with the fundamental equations that generate agglomeration economies. Sorting out these two possibilities is left as a challenge for future research.

²² For a modern version of von Thunen, see Samuelson's (1983) exposition. Davis and Weinstein (2002) conclude that nodality or natural advantage is a powerful force in determining the size and location of cities.

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Table 1a –	Summarv	statistics	in	levels	for al	ll MSAs.	(N=331))
I ubic Iu	Summury	Statistics		10,010	101 u		(1, 551)	,

	Min	Max	Mean	STD	CV
1970					
Skill Intensity Ratio	0.05	0.45	0.13	0.06	46.42
Median Owner's Value*	6.45	46.78	16.26	4.56	28.01
Median Gross Rent	57.00	199.00	101.44	20.23	19.94
Population*	27.56	9075.55	483.27	926.25	191.66
Manufacturing Share	0.03	0.57	0.24	0.12	48.48
Professional Services Share	0.10	0.49	0.19	0.06	29.76
Trade Share	0.13	0.30	0.21	0.03	13.31
1980					
Skill Intensity Ratio	0.08	0.63	0.20	0.09	43.43
Median Owner's Value*	24.19	130.41	47.68	16.13	33.83
Median Gross Rent	165.00	374.00	234.86	34.14	14.54
Population*	58.46	8274.96	536.40	935.07	174.32
Manufacturing Share	0.03	0.52	0.21	0.10	44.88
Professional Services Share	0.13	0.48	0.21	0.05	22.54
Trade Share	0.14	0.28	0.21	0.02	11.57
1990					
Skill Intensity Ratio	0.10	0.79	0.26	0.11	43.96
Median Owner's Value*	35.61	359.04	83.02	49.24	59.31
Median Gross Rent	278.00	820.00	421.87	103.04	24.42
Population*	56.74	8863.16	599.40	1023.51	170.75
Manufacturing Share	0.04	0.46	0.17	0.07	42.5
Professional Services Share	0.15	0.49	0.24	0.05	18.96
Trade Share	0.16	0.29	0.22	0.02	9.79
2000					
Skill Intensity Ratio	0.12	1.14	0.33	0.15	45.52
Median Owner's Value*	52.40	469.50	117.54	56.17	47.79
Median Gross Rent	363.00	1185.00	562.30	120.48	21.43
Population*	57.81	9519.34	682.72	1144.82	167.68
Manufacturing Share	0.03	0.43	0.15	0.06	43.57
Professional Services Share	0.15	0.39	0.24	0.03	14.24
Trade Share	0.16	0.31	0.22	0.02	9.92

*Divided by 1,000

	Min	Max	Mean	STD	CV
1970 to 1980					
Skill Intensity Ratio	1.60	11.13	5.93	1.57	26.46
Median Owner's Value	8.94	34.62	19.36	4.83	24.95
Median Gross Rent	6.67	25.93	13.53	2.81	20.78
Population	-0.88	12.60	1.90	1.94	101.88
Manufacturing Share	-4.82	9.30	-0.58	1.73	-295.91
Professional Services Share	-4.31	5.94	1.40	1.24	88.93
Trade Share	-1.28	2.32	0.23	0.63	271
1980 to 1990					
Skill Intensity Ratio	-0.03	9.54	2.73	1.22	44.79
Median Owner's Value	-2.51	26.02	6.94	5.41	77.9
Median Gross Rent	-0.89	14.33	7.85	2.54	32.34
Population	-1.48	8.98	1.19	1.51	127.19
Manufacturing Share	-5.64	2.24	-1.70	1.24	-72.98
Professional Services Share	-0.51	8.52	1.58	1.00	63.3
Trade Share	-1.21	4.91	0.54	0.75	139.36
1990 to 2000					
Skill Intensity Ratio	-0.90	6.35	2.53	1.00	39.65
Median Owner's Value	-1.12	13.61	4.99	2.79	55.88
Median Gross Rent	0.95	7.37	3.45	1.07	31.01
Population	-0.74	8.33	1.34	1.16	86.5
Manufacturing Share	-4.26	8.96	-1.35	1.23	-91.19
Professional Services Share	-3.39	1.95	-0.27	0.68	-250.92
Trade Share	-3.54	4.34	-0.20	0.64	-317.67

Table 1b – Summary statistics in annual growth rates (percents) for all MSAs, (N=331)

	Min	Max	Mean	STD	CV
1980 to 1990, (N=130)					
Skill Intensity Ratio	0.48	5.70	2.88	1.11	38.65
Median Owner's Value	0.19	23.52	7.33	5.20	70.99
House Price Index	-0.45	22.58	6.41	4.97	77.59
Median Gross Rent	1.56	14.03	8.36	2.58	30.85
Population	-0.87	6.61	1.52	1.50	98.48
Manufacturing Share	-4.17	1.60	-1.76	1.12	-63.96
Professional Services Share	-0.29	8.52	1.55	0.94	60.59
Trade Share	-0.80	1.84	0.39	0.57	144.71
1990 to 2000, (N=326)					
Skill Intensity Ratio	-0.90	5.51	2.52	1.01	40.07
Median Owner's Value	-1.07	13.61	5.42	2.75	50.77
House Price Index	-0.58	12.31	4.51	2.38	52.68
Median Gross Rent	1.11	7.37	3.54	1.05	29.62
Population	-0.55	8.61	1.55	1.33	86.16
Manufacturing Share	-4.60	6.31	-1.32	1.14	-86.69
Professional Services Share	-2.10	1.47	-0.30	0.67	-223.96
Trade Share	-3.26	4.52	-0.15	0.67	-455.19

Table 1c – Summary statistics in annual growth rates (percents): CBSAs with house price index values available from FHFA

Notes: *Skill Intensity Ratio* is the ratio of adults aged 25 years or older with at least a bachelor's degree to those with less education. For census years 1970 and 1980, completion of sixteen years of school defines attainment of a bachelor's. For 1990 and 2000, due to changes in Census Bureau survey questions, bachelor's attainment is based differently on receipt of degree. *House Price Index* is FHFA's "All Transactions" measure for cities. HUD's *State of the Cities Data System* tabulates *Median Owner's Value* and *Median Gross Rent* along with all other analysis variables, from decennial census microdata. The definition of "city" varies between the metropolitan statistical area (MSA) and the core-based statistical area (CBSA) depending on which measure of house price is included. For cities in New England States, the standard MSA/PMSA definition is followed, as opposed to the New England County Metropolitan Area (NECMA) definition.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent va	ariable: ln(S	Skill Intensit	y Ratio)		
ln(Median Value)	0.22***	-	0.25***	-	0.23***	-
	[12.35]		[14.25]		[14.64]	
ln(Median Rent)	-	0.36***	-	0.39***	-	0.45***
		[11.26]		[12.37]		[13.18]
ln(Population)	-	-	-0.08***	-0.10***	-0.07***	-0.15***
			[-4.11]	[-4.92]	[-3.22]	[-5.84]
ln(Manufact Share)	-	-	-0.20***	-0.22***	-0.11***	-0.11***
· · · ·			[-9.43]	[-10.35]	[-4.75]	[-4.34]
ln(Pro Services Share)	-	-	0.17***	0.04	0.18***	0.17***
			[4.74]	[1.07]	[4.34]	[4.15]
ln(<i>Trade Share</i>)	-	-	-0.14***	-0.12**	0.01	0.06
			[-2.86]	[-2.49]	[0.24]	[1.18]
(Skill Intensity Ratio) L1	-	-	-	-	0.69***	0.63***
					[9.27]	[8.17]
Constant	-4.27***	-3.97***	-4.22***	-3.80***	-3.75***	-2.97***
	[-20.02]	[-19.17]	[-15.27]	[-13.78]	[-11.61]	[-9.26]
	L]	[]	[]	[]	r 1	[]
R^2	0.98	0.98	0.98	0.98	0.99	0.99

 Table 2a – Panel regression coefficients, variables in levels

Models include MSA and time fixed effects

Cross section observations = 331

Time series = 4: 1970, 1980, 1990, and 2000 (Models 5 and 6 exclude 1970)

t-ratios in brackets

* p < 0.10, ** p < 0.05, *** p < 0.01

	(1)	(2)	(3)
Dependent variable	: ln(Skill In	ntensity Rati	<i>o</i>)
ln(HPI)	0.20***	0.19***	0.27***
	[7.93]	[7.34]	[7.20]
ln(<i>Population</i>)	-	-0.00	-0.06
		[-0.11]	[-0.86]
ln(Manufact Share)	-	-0.28***	-0.11*
		[-6.24]	[-1.96]
ln(Pro Services Share)	-	0.08	0.33***
		[0.96]	[3.12]
ln(<i>Trade Share</i>)	-	-0.20**	0.03
		[-2.14]	[0.31]
(Skill Intensity Ratio)_L1	-	-	1.08***
			[6.31]
Constant	-2.06***	-2.58***	-1.53
	[-15.88]	[-4.03]	[-1.57]
<i>R</i> ²	0.98	0.98	0.99

 Table 2b – Adding House Price Index to panel models

Models include CBSA and time fixed effects Cross section observations = 130 Time series = 3: 1980, 1990, and 2000 *t*-ratios in brackets * p < 0.10, ** p < 0.05, *** p < 0.01

Notes: The dependent variable is the log-ratio of adults aged 25 years or older with at least a bachelor's degree to those with less education. The first specification(s) include different house price measures, plus year and city dummies as the only explanatory variables. Next, conditioning variables are added to the model: population and three measures of industrial composition. The final specification(s) add level and lagged skill intensity. All values are from HUD's tabulation of decennial censuses.

	(1)	(2)	(3)	(4)	(5)	(6)
Ι	Dependent vari	able: $\Delta \ln(S)$	kill Intensity	Ratio)		
$\Delta \ln(Median \ Value)$	0.16***	-	0.19***	-	0.20***	-
	[12.09]		[13.80]		[16.16]	
$\Delta \ln(Median Rent)$	-	0.27***	-	0.30***	-	0.41***
		[10.36]		[11.31]		[13.99]
$\Delta \ln(Population)$	-	-	-0.07***	-0.09***	-0.05*	-0.11***
			[-3.14]	[-3.67]	[-1.83]	[-4.00]
$\Delta \ln(Manufact Share)$	-	-	-0.15***	-0.16***	-0.07***	-0.07***
			[-6.61]	[-7.52]	[-3.11]	[-2.89]
$\Delta \ln(Pro \ Services \ Share)$	-	-	0.15***	0.05	0.17***	0.18***
			[3.99]	[1.54]	[3.31]	[3.91]
$\Delta \ln(Trade Share)$	-	-	-0.19***	-0.19***	-0.01	0.00
			[-4.02]	[-3.85]	[-0.26]	[0.08]
Skill Intensity Ratio L1	-	-	-	-	0.12***	0.11***
· _					[5.19]	[5.18]
$\Delta \ln(Skill Intensity Ratio)$ L1	-	-	-	-	0.23***	0.21***
					[6.92]	[6.27]
Constant	0.16***	0.14***	0.14***	0.12***	0.05***	0.02*
	[24.11]	[16.21]	[18.64]	[13.52]	[4.53]	[1.93]
	L]					
Adjusted R ²	0.64	0.63	0.69	0.67	0.43	0.39

Table '	39 _	Pooled	OI S	regression	coefficients	variables	in	first	differences
Table.	3a –	rooleu	OLS	regression	coefficients,	variables	ш	mst	unificiences

Models include time fixed effects

Cross section observations = 331

Time series = 3: 1970 to 1980, 1980 to 1990, 1990 to 2000 (Models 5 and 6 exclude 1970 to 1980) *t*-ratios in brackets

* *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01

	(1)	(2)	(3)
Dependent variable:	$\Delta \ln(Skill International Inte$	tensity Ratio)
$\Delta \ln(House \ Price \ Index)$	0.16***	0.17***	0.18***
	[9.12]	[9.60]	[11.48]
$\Delta \ln(Population)$	-	-0.04	-0.03
		[-1.16]	[-0.91]
$\Delta \ln(Manufact Share)$	-	-0.15***	-0.09**
		[-4.20]	[-2.55]
$\Delta \ln(Pro \ Services \ Share)$	-	0.13**	0.18**
		[2.01]	[2.34]
$\Delta \ln(Trade Share)$	-	-0.24***	-0.15*
		[-2.83]	[-1.82]
Skill Intensity Ratio_L1	-	-	0.09***
			[3.55]
Δln(Skill Intensity Ratio) L1	-	-	0.32***
			[7.43]
Constant	0.16***	0.14***	0.05***
	[21.17]	[13.68]	[3.52]
Adjusted R^2	0.16	0.24	0.38

 Table 3b – Adding House Price Index to pooled OLS models

Models include time fixed effects

Cross section observations: N=130 (1980 to 1990), N=326 (1990 to 2000) *t*-ratios in brackets

* p < 0.10, ** p < 0.05, *** p < 0.01

Notes: The dependent variable is the change in the log-ratio of adults aged 25 years or older with at least a bachelor's degree to those with less education. The first specification(s) include different house price measures, plus year and city dummies as the only explanatory variables. Subsequent specifications add conditioning variables to the model. *House Price Index* is FHFA's "All Transactions" measure for cities. All other values are from HUD's tabulation of decennial censuses. *t*-Statistics are based on heteroskedasticity consistent standard errors.

	Prefe	erred	Growt	h Rate	Effect			
	Model	Elasticity	Mean	Dev.	Mean	Dev.		
Hour Price Measures								
Median Value	3a.3	0.186	104.3%	33.1%	19.4%	6.2%		
House Price Index	3b.2	0.169	50.5%	10.4%	8.5%	1.8%		
Median Rent	3a.4	0.299	82.8%	16.6%	24.8%	4.9%		
Conditioning Variables								
Population	3a.3, 3a.4	-0.083	14.8%	11.3%	-1.2%	-0.9%		
Manufact Share	3a.3, 3a.4	-0.155	-12.1%	10.0%	1.9%	-1.6%		
Pro Services Share	3a.3, 3a.4	0.099	9.0%	7.3%	0.9%	0.7%		
Trade Share	3a.3, 3a.4	-0.190	1.9%	5.0%	-0.4%	-1.0%		
Skill Intensity Ratio			37.3%	5.3%				
<i>House Price Index</i> : N=130 (1980 to 1990), N=326 (1990 to 2000)								

Table 4 – Comparing effect size of decadal growth rates (percents) in explanatory variables

All other variables

Cross section observations = 331

Time series = 3: 1970 to 1980, 1980 to 1990, 1990 to 2000

Notes: Effect is the product of the preferred elasticity estimate and the relevant statistic of the decadal growth rate. For conditioning variables, elasticity is the average of the values estimated by the indicated models. The statistic we are calling deviation measures the absolute value of the average dispersion from the average growth rate by time period (decade).

	(1)		(2)	(3)		
Data Source =>	HUD	IPUMS	HUD	IPUMS	HUD	IPUMS	
Dependent variable: Δln(Skill Intensity Ratio)							
$\Delta \ln(Median \ Value)$	0.17***	0.15***	-	-	-	-	
	[10.08]	[7.92]					
$\Delta \ln(Median Rent)$	-	-	0.36***	0.30***	-	-	
			[7.94]	[6.23]			
$\Delta \ln(House \ Price \ Index)$	-	-	-	-	0.17***	0.15***	
					[7.36]	[5.67]	
$\Delta \ln(Population)$	-0.08**	0.01	-0.14***	-0.02	-0.03	0.07	
	[-2.15]	[0.26]	[-3.27]	[-0.49]	[-0.65]	[1.58]	
$\Delta \ln(Manufact Share)$	-0.15***	-0.30***	-0.14***	-0.31***	-0.17***	-0.35***	
	[-3.81]	[-8.05]	[-3.61]	[-8.04]	[-3.38]	[-7.05]	
$\Delta \ln(Pro \ Services \ Share)$	0.13*	0.28***	0.15*	0.23**	0.23***	0.31***	
	[1.70]	[2.92]	[1.87]	[2.28]	[2.46]	[2.64]	
$\Delta \ln(Trade Share)$	-0.06	0.07	-0.04	0.04	-0.09	0.08	
	[-0.71]	[0.80]	[-0.45]	[0.44]	[-0.76]	[0.76]	
Constant	0.15***	0.07***	0.12***	0.05**	0.15***	0.05***	
	[13.14]	[3.45]	[8.52]	[2.09]	[10.06]	[2.46]	
Adjusted R ²	0.32	0.44	0.27	0.40	0.27	0.39	

Table 5a – Comparing pooled OLS regression coefficients estimated from census (HUD) data versus sample (IPUMS) data

Includes year fixed effects

Cross section observations = 131

Time series = 2: 1980 to 1990, 1990 to 2000

t-ratios in brackets

* *p* < 0.10, ** *p* < 0.05, *** *p* < 0.01

Notes: The HUD data are tabulations based on the entire adult population while the IPUMS data are estimates based on selected subsamples from the public use microsamples (IPUMS data). The dependent variable is the change in the log-ratio of adults (HUD) versus employed adults (IPUMS) aged 25 years or older with at least a bachelor's degree to those with less education. HUD model values are from HUD's tabulation of decennial censuses. IPUMS model values are from custom tabulations of public use decennial census microdata. Observations are cities with 1990 populations in excess of 250,000 (excluding Honolulu). t-Statistics are based on heteroskedasticity consistent standard errors.

	(1)	(2)	(3)
Estimation Method =>	OLS	2SLS	OLS	2SLS	OLS	2SLS
D	ependent varia	able: $\Delta \ln(Sh)$	cill Intensity	Ratio)		
$\Delta \ln(Median \ Value)$	0.19***	0.33**	-	-	-	-
	[11.81]	[2.51]				
$\Delta \ln(Median Rent)$	-	-	0.41***	0.73**	-	-
			[10.32]	[2.47]		
$\Delta \ln(House \ Price \ Index)$	-	-	-	-	0.18***	0.33*
					[8.28]	[1.74]
$\Delta \ln(Population)$	-0.07**	-0.13**	-0.13***	-0.24**	-0.06	-0.10*
	[-2.15]	[-2.03]	[-3.69]	[-2.26]	[-1.57]	[-1.75]
$\Delta \ln(Manufact Share)$	-0.11***	-0.05	-0.09***	-0.02	-0.14***	-0.11**
	[-3.95]	[-0.94]	[-3.24]	[-0.21]	[-3.36]	[-2.15]
$\Delta \ln(Pro \ Services \ Share)$	0.08	0.22	0.12**	0.30*	0.14**	0.29
	[1.44]	[1.59]	2.45	[1.78]	[1.99]	[1.48]
$\Delta \ln(Trade Share)$	-0.06	0.02	-0.02	0.11	-0.23**	-0.14
	[-0.99]	[0.26]	[-0.28]	[0.93]	[-2.48]	[-1.04]
Constant	0.13***	0.09***	0.10***	0.03	0.14***	0.10**
	[14.80]	[2.59]	[9.16]	[0.54]	[12.04]	[1.99]
Adjusted R ²	0.26	0.16	0.24	0.13	0.22	0.12
Includes year fixed effects						

Table 5b – Comparing pooled OLS regression coefficients and two-stage least squares regression coefficients

Models (1) and (2):

Cross section observations = 255

Time series = 2: 1980 to 1990, 1990 to 2000

Model (3):

Cross section observations: N=97 (1980 to 1990), N=282 (1990 to 2000)

t-ratios in brackets

* p < 0.10, ** p < 0.05, *** p < 0.01

Notes: The dependent variable is the change in the log-ratio of adults aged 25 years or older with at least a bachelor's degree to those with less education. Estimated alternately with pooled OLS and 2SLS instrumenting for the different measures of house price with an export price index due to Larson (2011). Unit of observation is the CBSA. State capitals and Washington, DC are excluded. *t*-Statistics are based on heteroskedasticity consistent standard errors.

Appendix

Table A.1 – Skill intensity ratio level and change by decade for all MSAs from 1970 to 2000

Abilene, TX 0.14 0.21 0.26 0.29 0.07 0.05 0.03 Akron, OH 0.12 0.18 0.24 0.32 0.06 0.06 0.08 Albany, GA 0.10 0.16 0.20 0.21 0.06 0.04 0.02 Albany-Schenectady-Troy, NY 0.14 0.22 0.31 0.39 0.09 0.09 0.08 Albuquerque, NM 0.18 0.26 0.33 0.40 0.08 0.07 0.07 Alexandria, LA 0.10 0.14 0.17 0.20 0.04 0.04 0.03 Allentown-Bethlehem-Easton, PA 0.09 0.15 0.21 0.27 0.06 0.06 0.06 Altoona, PA 0.06 0.09 0.12 0.16 0.03 0.03 0.04 Anchorage, AK 0.19 0.31 0.37 0.41 0.12 0.06 0.04 Ann Arbor, MI 0.24 0.36 0.45 0.59 0.12 0.06 0.04 Anniston, AL 0.08 0.12 0.17 0.18 0.04 0.04 0.01 Appleton-Oshkosh-Neenah, WI 0.10 0.16 0.23 0.32 0.06 0.06 0.07 Atlanta, GA 0.27 0.39 0.44 0.52 0.12 0.06 0.07 Atlanta, GA 0.27 0.39 0.44 0.52 0.12 0.06 0.07 Augusta-Aiken, GA-SC 0.11 0.16 0.22 0.26 0.0
Akron, OH 0.12 0.18 0.24 0.32 0.06 0.06 0.08 Albany, GA 0.10 0.16 0.20 0.21 0.06 0.04 0.02 Albany-Schenectady-Troy, NY 0.14 0.22 0.31 0.39 0.09 0.09 0.08 Albuquerque, NM 0.18 0.26 0.33 0.40 0.08 0.07 0.07 Alexandria, LA 0.10 0.14 0.17 0.20 0.04 0.04 0.03 Allentown-Bethlehem-Easton, PA 0.09 0.15 0.21 0.27 0.06 0.06 0.06 Altoona, PA 0.06 0.09 0.12 0.16 0.03 0.03 0.04 Anchorage, AK 0.19 0.23 0.27 0.05 0.04 0.04 Ann Arbor, MI 0.24 0.36 0.45 0.59 0.12 0.06 0.04 Appleton-Oshkosh-Neenah, WI 0.10 0.16 0.23 0.27 0.06 0.06 0.09 Athens, GA 0.27 0.39 0.44 0.52 0.12 0.06 0.04 0.09 Athens, GA 0.27 0.39 0.44 0.52 0.12 0.66 0.06 0.07 Atlanta, GA 0.14 0.25 0.35 0.47 0.10 0.11 0.12 Atlanta, GA 0.27 0.39 0.44 0.52 0.12 0.66 0.05 Austin-San Marcos, TX 0.20 0.28 0.34 0.39
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Baltimore, MD 0.11 0.20 0.30 0.41 0.09 0.10 0.11
Bangor, ME 0.14 0.22 0.30 0.36 0.08 0.08 0.06
Barnstable-Yarmouth, MA 0.19 0.31 0.40 0.50 0.12 0.09 0.11
Baton Rouge, LA 0.16 0.24 0.29 0.33 0.08 0.04 0.04
Beaumont-Port Arthur, TX 0.09 0.14 0.16 0.17 0.04 0.02 0.01
Bellingham, WA 0.12 0.22 0.28 0.37 0.10 0.06 0.09
Benton Harbor, MI 0.10 0.15 0.20 0.24 0.05 0.05 0.04
Bergen-Passaic, NJ 0.15 0.26 0.38 0.48 0.11 0.12 0.11
Billings, MT 0.15 0.25 0.27 0.36 0.10 0.03 0.08
Biloxi-Gulfport-Pascagoula, MS 0.10 0.14 0.18 0.21 0.04 0.04 0.03
Binghamton, NY 0.13 0.18 0.25 0.28 0.06 0.07 0.03
Birmingham, AL 0.10 0.18 0.24 0.33 0.08 0.07 0.08
Bismarck, ND 0.11 0.23 0.28 0.34 0.12 0.05 0.06
Bloomington, IN 0.38 0.46 0.49 0.66 0.08 0.04 0.17
Bloomington-Normal, IL 0.18 0.29 0.41 0.57 0.11 0.11 0.16
Boise City, ID 0.14 0.23 0.27 0.36 0.10 0.04 0.09
Boston, MA-NH 0.18 0.31 0.48 0.65 0.13 0.17 0.17
Boulder-Longmont, CO 0.36 0.59 0.75 1.14 0.23 0.16 0.39
Brazoria, TX 0.11 0.16 0.18 0.24 0.05 0.02 0.07
Bremerton, WA 0.11 0.20 0.25 0.34 0.08 0.05 0.09
Bridgeport, CT 0.11 0.20 0.30 0.39 0.09 0.10 0.09
Brockton, MA 0.09 0.15 0.21 0.28 0.06 0.06 0.07
Brownsville-Harlingen-San Benito, TX 0.08 0.12 0.14 0.15 0.04 0.02 0.02
Bryan-College Station, TX0.290.470.560.590.170.090.03

City	1970	1980	1990	2000	Δ1970	Δ1980	Δ1990
Buffalo-Niagara Falls, NY	0.11	0.17	0.23	0.30	0.06	0.06	0.07
Burlington, VT	0.19	0.31	0.44	0.59	0.12	0.13	0.15
Canton-Massillon, OH	0.07	0.12	0.16	0.21	0.05	0.04	0.05
Casper, WY	0.15	0.25	0.26	0.25	0.09	0.01	-0.01
Cedar Rapids, IA	0.13	0.20	0.27	0.38	0.07	0.07	0.11
Champaign-Urbana, IL	0.32	0.43	0.52	0.61	0.11	0.09	0.10
Charleston-North Charleston, SC	0.11	0.18	0.23	0.33	0.07	0.06	0.10
Charleston, WV	0.10	0.17	0.20	0.26	0.07	0.03	0.05
Charlotte-Gastonia-Rock Hill, NC-SC	0.10	0.17	0.24	0.36	0.07	0.07	0.12
Charlottesville, VA	0.24	0.40	0.50	0.67	0.16	0.10	0.17
Chattanooga, TN-GA	0.09	0.15	0.19	0.24	0.05	0.04	0.06
Cheyenne, WY	0.15	0.22	0.26	0.31	0.06	0.05	0.05
Chicago, IL	0.13	0.23	0.32	0.43	0.09	0.10	0.11
Chico-Paradise, CA	0.12	0.20	0.24	0.28	0.08	0.04	0.04
Cincinnati, OH-KY-IN	0.11	0.18	0.25	0.34	0.07	0.07	0.09
Clarksville-Hopkinsville, TN-KY	0.08	0.14	0.16	0.20	0.05	0.03	0.04
Cleveland-Lorain-Elyria, OH	0.11	0.17	0.23	0.30	0.06	0.05	0.08
Colorado Springs, CO	0.20	0.26	0.35	0.47	0.07	0.08	0.12
Columbia, MO	0.37	0.53	0.57	0.72	0.16	0.04	0.14
Columbia, SC	0.17	0.27	0.34	0.41	0.10	0.07	0.07
Columbus, GA-AL	0.10	0.13	0.18	0.23	0.04	0.04	0.05
Columbus, OH	0.14	0.23	0.30	0.41	0.08	0.08	0.11
Corpus Christi, TX	0.11	0.16	0.19	0.22	0.05	0.03	0.03
Corvallis, OR	0.42	0.58	0.70	0.90	0.16	0.13	0.20
Cumberland, MD-WV	0.07	0.10	0.13	0.16	0.03	0.03	0.03
Dallas, TX	0.16	0.27	0.37	0.43	0.11	0.10	0.06
Danbury, CT	0.19	0.37	0.56	0.65	0.18	0.18	0.09
Danville, VA	0.06	0.08	0.11	0.13	0.03	0.03	0.02
Davenport-Moline-Rock Island, IA-IL	0.10	0.17	0.21	0.25	0.07	0.04	0.04
Dayton-Springfield, OH	0.12	0.18	0.24	0.28	0.06	0.06	0.05
Daytona Beach, FL	0.12	0.15	0.18	0.22	0.03	0.03	0.04
Decatur, AL	0.07	0.11	0.15	0.19	0.04	0.04	0.03
Decatur, IL	0.10	0.15	0.17	0.20	0.05	0.02	0.03
Denver, CO	0.19	0.33	0.41	0.52	0.13	0.08	0.11
Des Moines, IA	0.14	0.22	0.29	0.40	0.09	0.07	0.11
Detroit, MI	0.10	0.16	0.21	0.29	0.06	0.05	0.08
Dothan, AL	0.08	0.14	0.17	0.20	0.06	0.03	0.03
Dover, DE	0.11	0.14	0.18	0.23	0.04	0.03	0.05
Dubuque, IA	0.11	0.18	0.20	0.27	0.06	0.03	0.07
Duluth-Superior, MN-WI	0.10	0.17	0.20	0.27	0.06	0.04	0.07
Dutchess County, NY	0.16	0.23	0.33	0.38	0.07	0.10	0.05
Eau Claire, WI	0.10	0.17	0.20	0.28	0.07	0.03	0.08
El Paso, TX	0.13	0.16	0.18	0.20	0.03	0.02	0.02
Elkhart-Goshen, IN	0.09	0.14	0.17	0.18	0.05	0.03	0.02
Elmira, NY	0.11	0.15	0.18	0.23	0.04	0.03	0.05
Enid, OK	0.12	0.19	0.21	0.24	0.07	0.02	0.03
Erie, PA	0.10	0.15	0.19	0.26	0.06	0.04	0.07
Eugene-Springfield, OR	0.17	0.26	0.29	0.34	0.09	0.03	0.06

City	1970	1980	1990	2000	Δ1970	Δ1980	Δ1990
Evansville-Henderson, IN-KY	0.09	0.14	0.17	0.23	0.05	0.04	0.05
Fargo-Moorhead, ND-MN	0.16	0.26	0.33	0.42	0.11	0.07	0.08
Fayetteville, NC	0.11	0.17	0.20	0.24	0.05	0.03	0.04
Fayetteville-Springdale-Rogers, AR	0.11	0.18	0.21	0.29	0.07	0.03	0.08
Fitchburg-Leominster, MA	0.07	0.12	0.20	0.24	0.05	0.08	0.04
Flagstaff, AZ-UT	0.19	0.29	0.31	0.42	0.10	0.02	0.10
Flint, MI	0.08	0.12	0.15	0.19	0.04	0.02	0.05
Florence, AL	0.08	0.13	0.17	0.20	0.05	0.04	0.03
Florence, SC	0.09	0.14	0.17	0.23	0.05	0.04	0.06
Fort Collins-Loveland, CO	0.24	0.40	0.48	0.65	0.16	0.07	0.18
Fort Lauderdale, FL	0.11	0.18	0.23	0.33	0.07	0.05	0.09
Fort Myers-Cape Coral, FL	0.11	0.15	0.20	0.27	0.04	0.04	0.07
Fort Pierce-Port St. Lucie, FL	0.09	0.15	0.19	0.25	0.06	0.04	0.05
Fort Smith, AR-OK	0.07	0.11	0.13	0.16	0.04	0.03	0.03
Fort Walton Beach, FL	0.15	0.20	0.27	0.32	0.05	0.07	0.05
Fort Wayne, IN	0.09	0.15	0.19	0.24	0.05	0.05	0.05
Fort Worth-Arlington, TX	0.13	0.21	0.29	0.33	0.08	0.08	0.05
Fresno, CA	0.11	0.17	0.19	0.20	0.06	0.02	0.01
Gadsden, AL	0.06	0.10	0.11	0.16	0.04	0.02	0.04
Gainesville, FL	0.30	0.42	0.53	0.63	0.12	0.11	0.10
Galveston-Texas City, TX	0.12	0.18	0.24	0.29	0.07	0.06	0.06
Gary, IN	0.07	0.12	0.16	0.22	0.05	0.04	0.05
Glens Falls, NY	0.10	0.15	0.18	0.23	0.05	0.03	0.05
Goldsboro, NC	0.08	0.12	0.15	0.18	0.05	0.02	0.03
Grand Forks, ND-MN	0.13	0.23	0.27	0.32	0.09	0.05	0.05
Grand Junction, CO	0.12	0.19	0.21	0.28	0.08	0.02	0.07
Grand Rapids-Muskegon-Holland, MI	0.10	0.17	0.22	0.30	0.07	0.05	0.08
Great Falls, MT	0.15	0.21	0.23	0.27	0.06	0.02	0.05
Greeley, CO	0.14	0.20	0.23	0.28	0.07	0.02	0.05
Green Bay, WI	0.11	0.17	0.21	0.29	0.06	0.05	0.07
GreensboroWinston-SalemHigh Point, NC	0.11	0.17	0.23	0.30	0.07	0.06	0.07
Greenville, NC	0.12	0.22	0.28	0.36	0.10	0.07	0.08
Greenville-Spartanburg-Anderson, SC	0.10	0.15	0.20	0.26	0.05	0.05	0.06
Hagerstown, MD	0.07	0.10	0.13	0.17	0.03	0.02	0.04
Hamilton-Middletown, OH	0.09	0.16	0.23	0.31	0.07	0.07	0.08
Harrisburg-Lebanon-Carlisle, PA	0.10	0.17	0.22	0.29	0.07	0.05	0.07
Hartford, CT	0.15	0.25	0.35	0.42	0.10	0.10	0.07
Hattiesburg, MS	0.13	0.20	0.25	0.32	0.07	0.05	0.07
Hickory-Morganton-Lenoir, NC	0.07	0.10	0.13	0.16	0.03	0.03	0.03
Honolulu, HI	0.18	0.28	0.33	0.39	0.09	0.05	0.06
Houma, LA	0.06	0.11	0.11	0.14	0.05	0.00	0.03
Houston, TX	0.16	0.29	0.33	0.37	0.13	0.04	0.04
Huntington-Ashland, WV-KY-OH	0.07	0.11	0.14	0.17	0.03	0.04	0.02
Huntsville, AL	0.20	0.23	0.37	0.45	0.04	0.14	0.08
Indianapolis, IN	0.11	0.18	0.25	0.35	0.07	0.07	0.10
Iowa City, IA	0.45	0.63	0.79	0.91	0.18	0.16	0.12
Jackson, MI	0.08	0.14	0.15	0.19	0.06	0.01	0.05
Jackson, MS	0.15	0.26	0.33	0.39	0.11	0.07	0.06

City	1970	1980	1990	2000	Δ1970	Δ1980	Δ1990
Jackson, TN	0.08	0.14	0.18	0.25	0.05	0.05	0.07
Jacksonville, FL	0.10	0.16	0.23	0.30	0.07	0.06	0.07
Jacksonville, NC	0.10	0.13	0.16	0.17	0.03	0.03	0.02
Jamestown, NY	0.08	0.13	0.17	0.20	0.05	0.03	0.04
Janesville-Beloit, WI	0.10	0.14	0.15	0.20	0.04	0.01	0.05
Jersey City, NJ	0.06	0.13	0.25	0.34	0.07	0.12	0.09
Johnson City-Kingsport-Bristol, TN-VA	0.08	0.12	0.16	0.20	0.05	0.04	0.04
Johnstown, PA	0.05	0.09	0.11	0.15	0.04	0.02	0.03
Jonesboro, AR	0.10	0.15	0.20	0.26	0.06	0.04	0.07
Joplin, MO	0.07	0.12	0.15	0.20	0.05	0.03	0.05
Kalamazoo-Battle Creek, MI	0.12	0.21	0.25	0.31	0.08	0.05	0.05
Kankakee, IL	0.07	0.12	0.14	0.18	0.05	0.02	0.04
Kansas City, MO-KS	0.13	0.22	0.30	0.40	0.09	0.09	0.10
Kenosha, WI	0.07	0.12	0.15	0.24	0.05	0.03	0.09
Killeen-Temple, TX	0.10	0.18	0.19	0.22	0.07	0.01	0.03
Knoxville, TN	0.11	0.19	0.24	0.31	0.07	0.05	0.06
Kokomo, IN	0.08	0.12	0.16	0.21	0.03	0.04	0.05
La Crosse, WI-MN	0.11	0.20	0.25	0.33	0.08	0.05	0.08
Lafayette, LA	0.09	0.16	0.18	0.21	0.07	0.02	0.03
Lafayette, IN	0.20	0.28	0.36	0.39	0.07	0.08	0.04
Lake Charles, LA	0.10	0.16	0.17	0.20	0.06	0.01	0.03
Lakeland-Winter Haven, FL	0.10	0.13	0.15	0.18	0.03	0.02	0.03
Lancaster, PA	0.09	0.15	0.20	0.26	0.06	0.05	0.06
Lansing-East Lansing, MI	0.18	0.28	0.33	0.40	0.10	0.05	0.07
Laredo, TX	0.07	0.11	0.13	0.16	0.04	0.02	0.04
Las Cruces, NM	0.19	0.24	0.28	0.29	0.05	0.04	0.01
Las Vegas, NV-AZ	0.11	0.14	0.15	0.20	0.03	0.02	0.04
Lawrence, KS	0.33	0.54	0.62	0.74	0.21	0.08	0.12
Lawrence, MA-NH	0.11	0.20	0.32	0.41	0.09	0.12	0.09
Lawton, OK	0.13	0.18	0.23	0.24	0.05	0.05	0.01
Lewiston-Auburn, ME	0.07	0.12	0.14	0.17	0.05	0.02	0.02
Lexington, KY	0.16	0.26	0.33	0.40	0.10	0.07	0.08
Lima, OH	0.07	0.11	0.12	0.16	0.04	0.02	0.03
Lincoln, NE	0.21	0.31	0.38	0.48	0.10	0.07	0.10
Little Rock-North Little Rock, AR	0.11	0.20	0.26	0.33	0.08	0.06	0.07
Longview-Marshall, TX	0.09	0.15	0.17	0.20	0.06	0.02	0.03
Los Angeles-Long Beach, CA	0.15	0.23	0.29	0.33	0.08	0.06	0.04
Louisville, KY-IN	0.09	0.16	0.21	0.28	0.06	0.05	0.08
Lowell, MA-NH	0.10	0.19	0.29	0.39	0.09	0.11	0.10
Lubbock, TX	0.16	0.25	0.31	0.32	0.09	0.05	0.02
Lynchburg, VA	0.09	0.15	0.19	0.24	0.06	0.04	0.05
Macon, GA	0.10	0.15	0.19	0.24	0.05	0.04	0.05
Madison, WI	0.30	0.45	0.52	0.68	0.15	0.07	0.17
Manchester, NH	0.09	0.18	0.29	0.37	0.10	0.11	0.08
Mansfield, OH	0.07	0.10	0.12	0.13	0.04	0.02	0.01
McAllen-Edinburg-Mission, TX	0.08	0.12	0.13	0.15	0.04	0.01	0.02
Medford-Ashland, OR	0.11	0.18	0.21	0.29	0.07	0.03	0.07
Melbourne-Titusville-Palm Bay, FL	0.18	0.21	0.26	0.31	0.03	0.05	0.05

Memphis, TN-AR-MS 0.10 0.17 0.23 0.29 0.07 0.06 0.06 Merced, CA 0.09 0.12 0.13 0.22 0.03 0.02 -0.01 Miami, FL 0.12 0.20 0.23 0.28 0.08 0.03 0.05 Middlesex-Somerset-Hunterdon, NJ 0.15 0.26 0.43 0.60 0.11 0.09 0.13 Missoula, MT 0.13 0.21 0.22 0.32 0.40 0.09 0.13 Mobile, AL 0.08 0.14 0.19 0.25 0.66 0.05 0.06 Modesto, CA 0.09 0.13 0.15 0.16 0.04 0.02 0.01 Monnoe, LA 0.12 0.21 0.27 0.33 0.09 0.06 0.06 Muncie, IN 0.11 0.18 0.23 0.29 0.99 0.04 0.06 0.00 Muncie, IN 0.11 0.18 0.23 0.27 0.37 0.06	City	1970	1980	1990	2000	Δ1970	Δ1980	Δ1990
Merced, CA 0.09 0.12 0.14 0.12 0.03 0.02 -0.01 Miami, FL 0.12 0.24 0.23 0.28 0.88 0.03 0.05 Middlesex-Somerset-Hunterdon, NJ 0.15 0.26 0.43 0.60 0.11 0.17 0.16 Mirwaukkee-Waukesha, WI 0.16 0.28 0.37 0.50 0.11 0.09 0.01 0.13 Mirssoula, MT 0.23 0.32 0.38 0.49 0.09 0.07 0.10 Modesto, CA 0.09 0.13 0.15 0.16 0.04 0.02 0.01 Monmouth-Occan, NJ 0.14 0.12 0.21 0.33 0.99 0.06 0.06 Montgomery, AL 0.12 0.11 0.18 0.23 0.27 0.33 0.07 0.05 0.04 Maples, FL 0.18 0.23 0.27 0.33 0.40 0.00 0.01 0.16 0.13 0.16 0.07 0.10	Memphis, TN-AR-MS	0.10	0.17	0.23	0.29	0.07	0.06	0.06
Miami, FL 0.12 0.20 0.23 0.28 0.03 0.05 Middlesex-Somerset-Hunterdon, NJ 0.15 0.26 0.43 0.60 0.11 0.17 0.16 Minwauke-Waukesha, WI 0.15 0.27 0.37 0.50 0.11 0.09 0.07 Missoula, MT 0.23 0.32 0.32 0.32 0.32 0.06 0.09 0.07 0.10 Mobile, AL 0.08 0.14 0.12 0.28 0.38 0.49 0.09 0.07 0.10 Momouth-Ocean, NJ 0.14 0.22 0.38 0.49 0.06 0.06 Muncie, IN 0.12 0.18 0.23 0.27 0.33 0.09 0.06 0.06 Muncie, IN 0.11 0.18 0.23 0.07 0.02 0.06 Muncie, IN 0.11 0.18 0.23 0.07 0.05 0.06 Muncie, IN 0.11 0.18 0.23 0.07 0.010 0.18	Merced, CA	0.09	0.12	0.14	0.12	0.03	0.02	-0.01
Middlesex-Somerset-Hunterdon, NJ 0.15 0.26 0.43 0.60 0.11 0.17 0.16 Milwaukee-Waukesha, WI 0.13 0.21 0.27 0.37 0.08 0.06 0.010 Missoula, MT 0.23 0.32 0.38 0.49 0.09 0.13 Mobile, AL 0.08 0.14 0.19 0.25 0.06 0.05 0.06 Modesto, CA 0.09 0.13 0.15 0.16 0.04 0.02 0.01 Monroe, LA 0.12 0.18 0.33 0.29 0.06 0.05 0.06 Montrogency, AL 0.12 0.11 0.18 0.23 0.29 0.06 0.06 0.06 Montrogency, AL 0.12 0.11 0.18 0.23 0.07 0.05 0.04 Naples, FL 0.18 0.23 0.29 0.39 0.04 0.06 0.10 0.10 Naskau, NH 0.16 0.21 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05	Miami, FL	0.12	0.20	0.23	0.28	0.08	0.03	0.05
Milwaukoc-Waukosha, WI 0.13 0.21 0.27 0.37 0.06 0.09 0.13 Minseoula, MT 0.23 0.32 0.32 0.34 0.49 0.09 0.07 0.10 Moissoula, MT 0.23 0.32 0.32 0.36 0.49 0.09 0.07 0.10 Moissoula, MT 0.23 0.32 0.34 0.49 0.02 0.06 0.06 Modesto, CA 0.09 0.13 0.15 0.16 0.04 0.02 0.01 Monnouth-Ocean, NJ 0.14 0.22 0.23 0.07 0.02 0.06 Muncic, IN 0.11 0.12 0.21 0.27 0.33 0.09 0.06 0.01 Nashua, NH 0.14 0.17 0.24 0.50 0.13 0.16 0.07 Nassaus-Suffölk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 New Bedford, MA 0.06 0.11 0.16 0.25 0.05 0.05 0.05 0.05 0.05 0.05 0.05 0.05	Middlesex-Somerset-Hunterdon, NJ	0.15	0.26	0.43	0.60	0.11	0.17	0.16
Minneapolis-St. Paul, MN-WI 0.16 0.28 0.37 0.50 0.11 0.09 0.03 Missoula, MT 0.23 0.32 0.38 0.49 0.09 0.07 0.10 Mobile, AL 0.08 0.14 0.12 0.18 0.14 0.22 0.29 0.38 0.08 0.08 0.09 Monroe, LA 0.12 0.12 0.21 0.27 0.33 0.09 0.06 0.05 Muncie, IN 0.11 0.18 0.20 0.26 0.07 0.02 0.06 Myrtle Beach, SC 0.08 0.14 0.19 0.23 0.07 0.05 0.04 Nashua, NH 0.11 0.18 0.23 0.29 0.04 0.06 0.07 0.05	Milwaukee-Waukesha, WI	0.13	0.21	0.27	0.37	0.08	0.06	0.10
Missoula, MT0.230.320.380.490.090.070.10Mobile, AL0.080.140.190.250.060.050.06Modesto, CA0.090.130.150.160.040.020.01Monmouth-Ocean, NJ0.140.220.290.380.080.080.09Monroore, LA0.120.180.230.290.060.050.06Muncie, IN0.110.180.200.260.070.020.06Myrle Beach, SC0.080.140.190.230.070.050.04Nashua, NH0.140.270.320.090.070.10Nassau-Suffolk, NY0.110.260.360.460.090.070.10Nassau-Suffolk, NY0.110.260.360.460.090.070.10New London-Norwich, CT-RI0.160.260.380.460.050.050.05New Urdan, NJ0.160.260.370.460.090.070.07New Orleans, LA0.110.190.240.290.080.050.05New Urdan, NJ0.160.250.370.460.090.070.07New Orleans, LA0.110.170.240.280.060.060.05New Orleans, LA0.110.180.230.370.460.090.070.07New Orleans, LA0.110.180.23<	Minneapolis-St. Paul, MN-WI	0.16	0.28	0.37	0.50	0.11	0.09	0.13
Mobile, AL 0.08 0.14 0.19 0.25 0.06 0.05 0.06 Modesto, CA 0.09 0.13 0.15 0.16 0.04 0.02 0.01 Monmouth-Ocean, NJ 0.14 0.22 0.29 0.38 0.08 0.09 Monroe, LA 0.12 0.12 0.27 0.33 0.06 0.05 0.06 Muncie, IN 0.11 0.18 0.23 0.29 0.39 0.04 0.06 Myrtle Beach, SC 0.08 0.14 0.19 0.23 0.07 0.05 0.04 Nashua, NH 0.14 0.27 0.37 0.09 0.07 0.10 New Bedford, MA 0.06 0.11 0.16 0.26 0.38 0.46 0.10 0.12 0.08 New Greans, LA 0.11 0.16 0.26 0.34 0.08 0.07 0.07 New Greans, LA 0.11 0.16 0.26 0.34 0.08 0.05 0.05 <t< td=""><td>Missoula, MT</td><td>0.23</td><td>0.32</td><td>0.38</td><td>0.49</td><td>0.09</td><td>0.07</td><td>0.10</td></t<>	Missoula, MT	0.23	0.32	0.38	0.49	0.09	0.07	0.10
Modesto, CA 0.09 0.13 0.15 0.16 0.04 0.02 0.01 Monmouth-Ocean, NJ 0.14 0.22 0.29 0.38 0.08 0.09 Monroe, LA 0.12 0.12 0.27 0.33 0.09 0.06 0.06 Muncie, IN 0.11 0.18 0.20 0.26 0.07 0.02 0.06 Myrtle Beach, SC 0.08 0.14 0.19 0.23 0.07 0.05 0.04 Nashua, NH 0.14 0.27 0.32 0.07 0.02 0.06 Nasswilf, TN 0.11 0.26 0.36 0.46 0.09 0.10 0.10 New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 New Haven-Meriden, CT 0.16 0.26 0.34 0.08 0.07 0.01 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New Haven-Meriden, CT 0.16 0.	Mobile, AL	0.08	0.14	0.19	0.25	0.06	0.05	0.06
Monmouth-Ocean, NJ 0.14 0.22 0.29 0.38 0.08 0.09 Monroc, LA 0.12 0.18 0.23 0.29 0.06 0.05 0.06 Montgomery, AL 0.12 0.21 0.27 0.33 0.09 0.06 0.06 Muncie, IN 0.11 0.18 0.23 0.29 0.04 0.06 0.01 Naples, FL 0.18 0.23 0.29 0.39 0.04 0.06 0.10 Nashua, NH 0.14 0.27 0.42 0.50 0.13 0.16 0.07 Nassau-Suffolk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 New London-Norwich, CT-RI 0.16 0.26 0.34 0.08 0.07 0.07 New Orleans, LA 0.11 0.13 0.23 0.33 0.41 0.10 0.08 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newark, NJ	Modesto, CA	0.09	0.13	0.15	0.16	0.04	0.02	0.01
Monroe, LA 0.12 0.18 0.23 0.29 0.06 0.05 0.06 Montgomery, AL 0.12 0.21 0.27 0.33 0.09 0.06 0.06 Muncie, IN 0.11 0.18 0.20 0.07 0.05 0.04 Naples, FL 0.18 0.23 0.29 0.39 0.04 0.06 0.10 Nashuile, TN 0.11 0.20 0.27 0.37 0.09 0.07 0.10 Nassau-Suffolk, NY 0.17 0.26 0.38 0.46 0.10 0.12 0.08 New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 0.05 New London-Norwich, CT-RI 0.12 0.20 0.26 0.34 0.08 0.07 0.07 New Orleans, LA 0.11 0.17 0.24 0.29 0.06 0.06 0.05 New York, NY 0.13 0.23 0.33 0.41 0.10 0.09 0.07 0.06	Monmouth-Ocean, NJ	0.14	0.22	0.29	0.38	0.08	0.08	0.09
Montgomery, AL 0.12 0.21 0.27 0.33 0.09 0.06 0.06 Muncie, IN 0.11 0.18 0.20 0.26 0.07 0.02 0.06 Naples, FL 0.18 0.23 0.29 0.39 0.04 0.06 0.10 Nashua, NH 0.14 0.27 0.42 0.50 0.13 0.16 0.07 Nassau-Suffolk, NY 0.11 0.26 0.36 0.46 0.09 0.10 0.10 Nessau-Suffolk, NY 0.11 0.12 0.26 0.36 0.46 0.09 0.07 0.10 New Bedford, MA 0.06 0.11 0.16 0.21 0.08 0.07 0.07 New Orleans, LA 0.11 0.12 0.28 0.34 0.08 0.07 0.07 New Vork, NY 0.13 0.23 0.33 0.41 0.10 0.08 0.05 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.25 0.31	Monroe, LA	0.12	0.18	0.23	0.29	0.06	0.05	0.06
Muncie, IN 0.11 0.18 0.20 0.26 0.07 0.02 0.06 Myrle Beach, SC 0.08 0.14 0.19 0.23 0.29 0.39 0.04 0.06 0.10 Nashua, NH 0.14 0.27 0.42 0.50 0.13 0.16 0.07 Nashua, NH 0.11 0.20 0.27 0.37 0.99 0.07 0.10 Nessau-Suffolk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 0.05 New Haven-Meriden, CT 0.16 0.26 0.38 0.46 0.10 0.12 0.08 New Orleans, LA 0.11 0.17 0.24 0.29 0.08 0.05 0.05 New burgh, NY-PA 0.13 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Nerdik-Virginia Beach-Newport News, VA-NC 0.11 0.17 0.24<	Montgomery, AL	0.12	0.21	0.27	0.33	0.09	0.06	0.06
Myrtle Beach, SC 0.08 0.14 0.19 0.23 0.07 0.05 0.04 Naples, FL 0.18 0.23 0.29 0.39 0.04 0.06 0.10 Nashua, NH 0.14 0.27 0.42 0.50 0.13 0.16 0.07 Nashville, TN 0.11 0.20 0.27 0.37 0.09 0.07 0.10 Nassau-Suffolk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 0.05 New London-Norwich, CT-RI 0.12 0.026 0.34 0.08 0.07 0.08 Newark, NJ 0.13 0.23 0.33 0.41 0.10 0.08 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.31 0.43 0.12 0.12 0.11	Muncie, IN	0.11	0.18	0.20	0.26	0.07	0.02	0.06
Naples, FL 0.18 0.23 0.29 0.39 0.04 0.06 0.10 Nashua, NH 0.14 0.27 0.42 0.50 0.13 0.16 0.07 Nashville, TN 0.11 0.20 0.27 0.37 0.09 0.07 0.10 Nassau-Suffolk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 News London-Norwich, CT-RI 0.12 0.26 0.34 0.08 0.07 0.07 New London-Norwich, CT-RI 0.12 0.20 0.26 0.34 0.08 0.07 0.07 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newburgh, NY-PA 0.11 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.10 0.17 0.24 0.28 0.06 0.00 0.0	Myrtle Beach, SC	0.08	0.14	0.19	0.23	0.07	0.05	0.04
Nashua, NH 0.14 0.27 0.42 0.50 0.13 0.16 0.07 Nashville, TN 0.11 0.20 0.27 0.37 0.09 0.07 0.10 Nassau-Suffolk, NY 0.16 0.21 0.25 0.37 0.09 0.10 0.10 New Bedford, MA 0.06 0.16 0.21 0.05 0.05 0.05 New Haven-Meriden, CT 0.16 0.26 0.38 0.46 0.10 0.12 0.08 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.13 0.23 0.33 0.41 0.10 0.10 0.08 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.17 0.24 0.28 0.06 0.07 0.06 0.07 Oakland, CA 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.22 0.29 0.39	Naples, FL	0.18	0.23	0.29	0.39	0.04	0.06	0.10
Nashville, TN 0.11 0.20 0.27 0.37 0.09 0.07 0.10 Nassau-Suffolk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 0.05 New Haven-Meriden, CT 0.16 0.26 0.38 0.46 0.10 0.12 0.08 New London-Norwich, CT-RI 0.12 0.20 0.26 0.34 0.08 0.07 0.07 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.31 0.43 0.54 0.12 0.12 0.11 0.13 0.26 0.31 0.07 0.00 0.00	Nashua, NH	0.14	0.27	0.42	0.50	0.13	0.16	0.07
Nassau-Suffolk, NY 0.17 0.26 0.36 0.46 0.09 0.10 0.10 New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 0.05 New Haven-Meriden, CT 0.16 0.26 0.38 0.08 0.07 0.07 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.13 0.23 0.33 0.41 0.10 0.08 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.28 0.32 0.08 0.04 0.05 Olympia, WA 0.16 0.26 0.33 0.43 0.10 0.07 0	Nashville, TN	0.11	0.20	0.27	0.37	0.09	0.07	0.10
New Bedford, MA 0.06 0.11 0.16 0.21 0.05 0.05 New Haven-Meriden, CT 0.16 0.26 0.38 0.46 0.10 0.12 0.08 New London-Norwich, CT-RI 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.13 0.23 0.41 0.10 0.10 0.08 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.31 0.43 0.54 0.12 0.12 0.11 0.16 0.22 0.23 0.05 0.02 0.00 Odaland, CA 0.16 0.21 0.23 0.23 0.24 0.29 0.39 0.05 0.02 0.0	Nassau-Suffolk, NY	0.17	0.26	0.36	0.46	0.09	0.10	0.10
New Haven-Meriden, CT 0.16 0.26 0.38 0.46 0.10 0.12 0.08 New London-Norwich, CT-RI 0.12 0.20 0.26 0.34 0.08 0.07 0.07 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.13 0.23 0.33 0.41 0.10 0.10 0.08 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.07 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.16 0.03 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.28 0.32 0.08 0.04 0.05 Olympia, WA 0.16 0.26 0.33 0.07 <td< td=""><td>New Bedford, MA</td><td>0.06</td><td>0.11</td><td>0.16</td><td>0.21</td><td>0.05</td><td>0.05</td><td>0.05</td></td<>	New Bedford, MA	0.06	0.11	0.16	0.21	0.05	0.05	0.05
New London-Norwich, CT-RI 0.12 0.20 0.26 0.34 0.08 0.07 0.07 New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.13 0.23 0.33 0.41 0.10 0.10 0.08 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.25 0.31 0.07 0.06 0.07 Oakland, CA 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.16 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.16 0.21 0.23 0.23 0.32 0.08 0.04 0.05 Olympia, WA 0.16 0.22 0.29 0.39 0.45 0.10 0.07 0.10 Orange County, CA 0.19 0.21 <td>New Haven-Meriden, CT</td> <td>0.16</td> <td>0.26</td> <td>0.38</td> <td>0.46</td> <td>0.10</td> <td>0.12</td> <td>0.08</td>	New Haven-Meriden, CT	0.16	0.26	0.38	0.46	0.10	0.12	0.08
New Orleans, LA 0.11 0.19 0.24 0.29 0.08 0.05 0.05 New York, NY 0.13 0.23 0.33 0.41 0.10 0.10 0.08 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.07 Oakland, CA 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.16 0.03 0.02 0.03 Odessa-Midland, TX 0.16 0.21 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.28 0.32 0.08 0.04 0.05 Olympia, WA 0.16 0.21 0.23 0.23 0.04 0.06 0.07 0.10 Orange County, CA 0.19 0.26 0.33 0.07 0.07 0.07	New London-Norwich, CT-RI	0.12	0.20	0.26	0.34	0.08	0.07	0.07
New York, NY 0.13 0.23 0.33 0.41 0.10 0.10 0.08 Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.07 Oakland, CA 0.18 0.31 0.43 0.54 0.12 0.11 0.11 Ocala, FL 0.08 0.11 0.13 0.43 0.54 0.12 0.12 0.11 Ocassa-Midland, TX 0.16 0.21 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.28 0.32 0.08 0.04 0.05 Olympia, WA 0.16 0.26 0.33 0.43 0.10 0.07 0.10 Orange County, CA 0.19 0.29 0.39 0.45 0.10 0.09 0.06 Orlando, FL 0.10 0.12 0.16 0.21 0.03 0.07 0.07 Owensboro, KY 0.10 0.12 0.16 0.21 0.03<	New Orleans, LA	0.11	0.19	0.24	0.29	0.08	0.05	0.05
Newark, NJ 0.16 0.25 0.37 0.46 0.09 0.11 0.09 Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.07 Oakland, CA 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.16 0.03 0.02 0.03 Odessa-Midland, TX 0.16 0.21 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.16 0.21 0.23 0.22 0.08 0.04 0.05 Olympia, WA 0.16 0.26 0.33 0.43 0.10 0.07 0.10 Orange County, CA 0.19 0.29 0.39 0.09 0.07 0.10 Orange County, CA 0.19 0.29 0.39 0.45 0.10 0.09 0.06 Orlando, FL 0.12 0.16 0.21 0.03 0.04 0.04 Panama City, FL 0.10 0.17 0.22 0.27 0.06 0.06 0.05 <td>New York, NY</td> <td>0.13</td> <td>0.23</td> <td>0.33</td> <td>0.41</td> <td>0.10</td> <td>0.10</td> <td>0.08</td>	New York, NY	0.13	0.23	0.33	0.41	0.10	0.10	0.08
Newburgh, NY-PA 0.11 0.17 0.24 0.28 0.06 0.06 0.05 Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.21 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.16 0.03 0.02 0.03 Odessa-Midland, TX 0.16 0.21 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.23 0.05 0.02 0.00 Olmaha, NE-IA 0.16 0.21 0.23 0.28 0.32 0.08 0.04 0.05 Olmaha, NE-IA 0.13 0.22 0.29 0.39 0.09 0.07 0.10 Orange County, CA 0.19 0.29 0.39 0.45 0.10 0.07 0.07 Owensboro, KY 0.10 0.12 0.16 0.21 0.03 0.04 0.04 Paraersburg-Marietta, WV-OH 0.08 0.13 0.15	Newark, NJ	0.16	0.25	0.37	0.46	0.09	0.11	0.09
Norfolk-Virginia Beach-Newport News, VA-NC 0.11 0.18 0.25 0.31 0.07 0.06 0.07 Oakland, CA 0.18 0.31 0.43 0.54 0.12 0.12 0.11 Ocala, FL 0.08 0.11 0.13 0.16 0.03 0.02 0.03 Odessa-Midland, TX 0.16 0.21 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.23 0.03 0.04 0.05 Olympia, WA 0.16 0.26 0.33 0.43 0.10 0.07 0.10 Orange County, CA 0.19 0.29 0.39 0.45 0.10 0.09 0.06 Orlando, FL 0.12 0.19 0.26 0.33 0.07 0.07 0.07 Owensboro, KY 0.10 0.15 0.19 0.21 0.05 0.03 0.02 Panama City, FL 0.10 0.17 0.22 0.27 0.06 0.06 0.05	Newburgh, NY-PA	0.11	0.17	0.24	0.28	0.06	0.06	0.05
Oakland, CA0.180.310.430.540.120.120.11Ocala, FL0.080.110.130.160.030.020.03Odessa-Midland, TX0.160.210.230.230.050.020.00Oklahoma City, OK0.150.230.230.230.050.020.00Olympia, WA0.160.260.330.430.100.070.10Ornand, NE-IA0.130.220.290.390.090.070.10Orange County, CA0.190.290.390.450.100.090.06Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.060.06Pihladelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pittsfield, MA0.120.190.250.320.060.070.08Pittsfield, MA0.120.190.25 <td>Norfolk-Virginia Beach-Newport News, VA-NC</td> <td>0.11</td> <td>0.18</td> <td>0.25</td> <td>0.31</td> <td>0.07</td> <td>0.06</td> <td>0.07</td>	Norfolk-Virginia Beach-Newport News, VA-NC	0.11	0.18	0.25	0.31	0.07	0.06	0.07
Ocala, FL0.080.110.130.160.030.020.03Odessa-Midland, TX0.160.210.230.230.050.020.00Oklahoma City, OK0.150.230.280.320.080.040.05Olympia, WA0.160.260.330.430.100.070.10Omaha, NE-IA0.130.220.290.390.090.070.10Orage County, CA0.190.220.290.390.450.100.090.06Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsbield, MA0.120.190.250.320.060.070.08Portland, ME0.130.230.380.510.100.150.13Portland, ME0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.	Oakland, CA	0.18	0.31	0.43	0.54	0.12	0.12	0.11
Odessa-Midland, TX 0.16 0.21 0.23 0.23 0.05 0.02 0.00 Oklahoma City, OK 0.15 0.23 0.28 0.32 0.08 0.04 0.05 Olympia, WA 0.16 0.26 0.33 0.43 0.10 0.07 0.10 Omaha, NE-IA 0.13 0.22 0.29 0.39 0.09 0.07 0.10 Orange County, CA 0.19 0.22 0.29 0.39 0.45 0.10 0.09 0.06 Orlando, FL 0.12 0.19 0.26 0.33 0.07 0.07 0.07 Owensboro, KY 0.10 0.12 0.16 0.21 0.03 0.04 0.04 Panama City, FL 0.10 0.15 0.19 0.21 0.05 0.03 0.02 Pensacola, FL 0.10 0.17 0.22 0.27 0.06 0.06 0.05 Peoria-Pekin, IL 0.10 0.17 0.22 0.27 0.06 0.04 0.06 Philadelphia, PA-NJ 0.12 0.20 0.29 0.38 0.08 0.09 0.09 Phoenix-Mesa, AZ 0.14 0.22 0.27 0.36 0.04 0.06 Pine Bluff, AR 0.08 0.14 0.17 0.19 0.05 0.04 0.06 Pittsfield, MA 0.12 0.19 0.25 0.32 0.06 0.07 0.06 Poctatello, ID 0.13 0.23 0.38 0.51 0.10 $0.$	Ocala, FL	0.08	0.11	0.13	0.16	0.03	0.02	0.03
Oklahoma City, OK0.150.230.280.320.080.040.05Olympia, WA0.160.260.330.430.100.070.10Omaha, NE-IA0.130.220.290.390.090.070.10Orange County, CA0.190.290.390.450.100.090.06Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.03Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsfield, MA0.120.190.250.320.060.070.08Portland, ME0.130.230.380.510.100.150.13Portland, ME0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.23 <t< td=""><td>Odessa-Midland, TX</td><td>0.16</td><td>0.21</td><td>0.23</td><td>0.23</td><td>0.05</td><td>0.02</td><td>0.00</td></t<>	Odessa-Midland, TX	0.16	0.21	0.23	0.23	0.05	0.02	0.00
Olympia, WA0.160.260.330.430.100.070.10Omaha, NE-IA0.130.220.290.390.090.070.10Orange County, CA0.190.290.390.450.100.090.06Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsfield, MA0.120.190.250.320.060.070.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Oklahoma City, OK	0.15	0.23	0.28	0.32	0.08	0.04	0.05
Omaha, NE-IA0.130.220.290.390.090.070.10Orange County, CA0.190.290.390.450.100.090.06Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.03Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsbrigh, PA0.100.160.230.310.060.070.08Portland, ME0.130.230.380.510.100.150.13Portland, ME0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Olympia, WA	0.16	0.26	0.33	0.43	0.10	0.07	0.10
Orange County, CA0.190.290.390.450.100.090.06Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.03Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsfield, MA0.120.190.250.320.060.070.08Portland, ME0.130.230.380.510.100.150.13Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Omaha, NE-IA	0.13	0.22	0.29	0.39	0.09	0.07	0.10
Orlando, FL0.120.190.260.330.070.070.07Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.03Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsfield, MA0.120.190.250.320.060.070.08Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Orange County, CA	0.19	0.29	0.39	0.45	0.10	0.09	0.06
Owensboro, KY0.100.120.160.210.030.040.04Panama City, FL0.100.150.190.210.050.030.03Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.340.410.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Orlando, FL	0.12	0.19	0.26	0.33	0.07	0.07	0.07
Panama City, FL0.100.150.190.210.050.030.03Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.380.510.100.150.13Portland, ME0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Owensboro, KY	0.10	0.12	0.16	0.21	0.03	0.04	0.04
Parkersburg-Marietta, WV-OH0.080.130.150.180.050.030.02Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Panama City, FL	0.10	0.15	0.19	0.21	0.05	0.03	0.03
Pensacola, FL0.100.170.220.270.060.060.05Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.08Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Parkersburg-Marietta, WV-OH	0.08	0.13	0.15	0.18	0.05	0.03	0.02
Peoria-Pekin, IL0.100.170.200.270.060.040.06Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Pensacola, FL	0.10	0.17	0.22	0.27	0.06	0.06	0.05
Philadelphia, PA-NJ0.120.200.290.380.080.090.09Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Peoria-Pekin, IL	0.10	0.17	0.20	0.27	0.06	0.04	0.06
Phoenix-Mesa, AZ0.140.220.270.330.070.060.06Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Philadelphia, PA-NJ	0.12	0.20	0.29	0.38	0.08	0.09	0.09
Pine Bluff, AR0.080.140.170.190.050.040.01Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Phoenix-Mesa, AZ	0.14	0.22	0.27	0.33	0.07	0.06	0.06
Pittsburgh, PA0.100.160.230.310.060.070.08Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Pine Bluff, AR	0.08	0.14	0.17	0.19	0.05	0.04	0.01
Pittsfield, MA0.120.190.250.320.060.070.06Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Pittsburgh, PA	0.10	0.16	0.23	0.31	0.06	0.07	0.08
Pocatello, ID0.130.230.250.330.100.020.08Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Pittsfield, MA	0.12	0.19	0.25	0.32	0.06	0.07	0.06
Portland, ME0.130.230.380.510.100.150.13Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Pocatello, ID	0.13	0.23	0.25	0.33	0.10	0.02	0.08
Portland-Vancouver, OR-WA0.140.240.300.410.100.060.10Portsmouth-Rochester, NH-ME0.140.230.340.470.090.110.14	Portland, ME	0.13	0.23	0.38	0.51	0.10	0.15	0.13
Portsmouth-Rochester, NH-ME 0.14 0.23 0.34 0.47 0.09 0.11 0.14	Portland-Vancouver, OR-WA	0.14	0.24	0.30	0.41	0.10	0.06	0.10
	Portsmouth-Rochester, NH-ME	0.14	0.23	0.34	0.47	0.09	0.11	0.14

City	1970	1980	1990	2000	Δ1970	Δ1980	Δ1990
Providence-Fall River-Warwick, RI-MA	0.09	0.16	0.24	0.31	0.07	0.08	0.06
Provo-Orem, UT	0.19	0.31	0.36	0.46	0.11	0.05	0.10
Pueblo, CO	0.09	0.15	0.16	0.22	0.06	0.01	0.06
Punta Gorda, FL	0.10	0.15	0.16	0.21	0.05	0.01	0.06
Racine, WI	0.10	0.16	0.20	0.25	0.07	0.03	0.06
Raleigh-Durham-Chapel Hill, NC	0.18	0.31	0.46	0.64	0.13	0.15	0.17
Rapid City, SD	0.12	0.22	0.27	0.33	0.10	0.04	0.06
Reading, PA	0.07	0.13	0.18	0.23	0.06	0.05	0.05
Redding, CA	0.09	0.14	0.16	0.20	0.05	0.02	0.04
Reno, NV	0.16	0.25	0.26	0.31	0.09	0.02	0.05
Richland-Kennewick-Pasco, WA	0.16	0.25	0.27	0.30	0.09	0.01	0.04
Richmond-Petersburg, VA	0.13	0.23	0.31	0.41	0.10	0.09	0.10
Riverside-San Bernardino, CA	0.11	0.15	0.17	0.19	0.04	0.02	0.02
Roanoke, VA	0.11	0.17	0.22	0.29	0.06	0.05	0.07
Rochester, MN	0.22	0.33	0.42	0.53	0.11	0.09	0.11
Rochester, NY	0.15	0.23	0.30	0.37	0.08	0.07	0.08
Rockford, IL	0.09	0.15	0.18	0.23	0.06	0.04	0.04
Rocky Mount, NC	0.06	0.10	0.13	0.16	0.04	0.02	0.03
Sacramento, CA	0.14	0.23	0.29	0.35	0.09	0.06	0.05
Saginaw-Bay City-Midland, MI	0.10	0.14	0.18	0.22	0.04	0.03	0.04
St. Cloud, MN	0.10	0.16	0.20	0.27	0.06	0.04	0.06
St. Joseph, MO	0.07	0.12	0.16	0.21	0.05	0.04	0.05
St. Louis, MO-IL	0.11	0.18	0.26	0.34	0.07	0.07	0.08
Salem, OR	0.14	0.21	0.22	0.26	0.07	0.01	0.04
Salinas, CA	0.18	0.24	0.27	0.29	0.07	0.03	0.02
Salt Lake City-Ogden, UT	0.17	0.26	0.30	0.36	0.09	0.04	0.06
San Angelo, TX	0.11	0.17	0.20	0.24	0.06	0.03	0.04
San Antonio, TX	0.11	0.18	0.24	0.29	0.07	0.05	0.05
San Diego, CA	0.16	0.26	0.34	0.42	0.10	0.08	0.08
San Francisco, CA	0.22	0.40	0.54	0.77	0.18	0.13	0.24
San Jose, CA	0.24	0.36	0.48	0.68	0.12	0.13	0.20
San Luis Obispo-Atascadero-Paso Robles, CA	0.13	0.23	0.30	0.36	0.11	0.06	0.07
Santa Barbara-Santa Maria-Lompoc, CA	0.22	0.33	0.36	0.42	0.11	0.04	0.05
Santa Cruz-Watsonville, CA	0.15	0.31	0.42	0.52	0.15	0.12	0.10
Santa Fe, NM	0.27	0.46	0.55	0.66	0.18	0.10	0.11
Santa Rosa, CA	0.12	0.24	0.32	0.40	0.11	0.09	0.07
Sarasota-Bradenton, FL	0.14	0.18	0.24	0.33	0.05	0.05	0.09
Savannah, GA	0.09	0.15	0.21	0.30	0.06	0.06	0.09
ScrantonWilkes-BarreHazleton, PA	0.06	0.11	0.16	0.21	0.05	0.05	0.05
Seattle-Bellevue-Everett, WA	0.19	0.31	0.42	0.56	0.12	0.11	0.14
Sharon, PA	0.08	0.13	0.16	0.21	0.05	0.02	0.05
Sheboygan, WI	0.07	0.13	0.16	0.22	0.05	0.03	0.06
Sherman-Denison, TX	0.10	0.15	0.16	0.21	0.05	0.01	0.05
Shreveport-Bossier City, LA	0.11	0.17	0.20	0.24	0.06	0.03	0.04
Sioux City, IA-NE	0.10	0.16	0.19	0.22	0.06	0.03	0.03
Sioux Falls, SD	0.11	0.19	0.26	0.35	0.08	0.07	0.09
South Bend, IN	0.11	0.17	0.24	0.31	0.07	0.07	0.07
Spokane, WA	0.13	0.22	0.26	0.33	0.08	0.04	0.07

City	1970	1980	1990	2000	Δ1970	Δ1980	Δ1990
Springfield, IL	0.11	0.22	0.28	0.39	0.11	0.06	0.11
Springfield, MO	0.10	0.16	0.23	0.29	0.07	0.06	0.06
Springfield, MA	0.12	0.20	0.26	0.33	0.08	0.07	0.06
Stamford-Norwalk, CT	0.33	0.50	0.76	0.98	0.17	0.26	0.22
State College, PA	0.30	0.38	0.48	0.57	0.08	0.10	0.09
Steubenville-Weirton, OH-WV	0.05	0.09	0.10	0.14	0.03	0.02	0.03
Stockton-Lodi, CA	0.09	0.13	0.15	0.17	0.04	0.02	0.02
Sumter, SC	0.10	0.13	0.18	0.19	0.02	0.05	0.01
Syracuse, NY	0.14	0.20	0.26	0.32	0.06	0.06	0.06
Tacoma, WA	0.11	0.18	0.21	0.26	0.07	0.03	0.05
Tallahassee, FL	0.22	0.36	0.48	0.58	0.14	0.11	0.10
Tampa-St. Petersburg-Clearwater, FL	0.10	0.15	0.21	0.28	0.05	0.05	0.07
Terre Haute, IN	0.09	0.16	0.18	0.23	0.07	0.02	0.05
Texarkana, TX-Texarkana, AR	0.07	0.12	0.15	0.18	0.04	0.03	0.03
Toledo, OH	0.10	0.17	0.21	0.28	0.06	0.04	0.06
Topeka, KS	0.15	0.25	0.29	0.35	0.09	0.04	0.06
Trenton, NJ	0.16	0.28	0.42	0.51	0.11	0.14	0.10
Tucson, AZ	0.19	0.26	0.30	0.37	0.07	0.04	0.06
Tulsa, OK	0.12	0.21	0.26	0.30	0.08	0.05	0.05
Tuscaloosa, AL	0.12	0.20	0.25	0.32	0.08	0.05	0.07
Tyler, TX	0.11	0.19	0.25	0.29	0.08	0.06	0.04
Utica-Rome, NY	0.10	0.14	0.19	0.22	0.05	0.04	0.03
Vallejo-Fairfield-Napa, CA	0.11	0.18	0.25	0.29	0.07	0.07	0.05
Ventura, CA	0.14	0.22	0.30	0.37	0.08	0.08	0.07
Victoria, TX	0.10	0.14	0.16	0.19	0.04	0.03	0.03
Vineland-Millville-Bridgeton, NJ	0.06	0.10	0.12	0.13	0.04	0.03	0.01
Visalia-Tulare-Porterville, CA	0.08	0.11	0.13	0.13	0.04	0.02	0.00
Waco, TX	0.11	0.17	0.20	0.24	0.06	0.03	0.04
Washington, DC-MD-VA-WV	0.28	0.44	0.59	0.72	0.16	0.14	0.13
Waterbury, CT	0.09	0.16	0.23	0.27	0.06	0.08	0.04
Waterloo-Cedar Falls, IA	0.11	0.18	0.21	0.30	0.07	0.03	0.09
Wausau, WI	0.08	0.13	0.16	0.22	0.05	0.02	0.07
West Palm Beach-Boca Raton, FL	0.14	0.21	0.28	0.38	0.07	0.08	0.10
Wheeling, WV-OH	0.06	0.10	0.14	0.17	0.04	0.04	0.03
Wichita, KS	0.14	0.22	0.27	0.33	0.08	0.06	0.05
Wichita Falls, TX	0.12	0.16	0.19	0.25	0.04	0.03	0.05
Williamsport, PA	0.08	0.12	0.14	0.18	0.04	0.02	0.04
Wilmington-Newark, DE-MD	0.16	0.24	0.31	0.38	0.08	0.07	0.07
Wilmington, NC	0.09	0.17	0.22	0.35	0.07	0.05	0.13
Worcester, MA-CT	0.10	0.19	0.30	0.38	0.09	0.10	0.09
Yakima, WA	0.09	0.13	0.16	0.18	0.03	0.03	0.02
Yolo, CA	0.23	0.37	0.43	0.52	0.14	0.06	0.08
York, PA	0.07	0.13	0.16	0.23	0.05	0.03	0.06
Youngstown-Warren, OH	0.07	0.11	0.14	0.18	0.04	0.02	0.04
Yuba City, CA	0.10	0.14	0.15	0.15	0.03	0.01	0.01
Yuma, AZ	0.10	0.12	0.15	0.13	0.03	0.02	-0.01