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INDUSTRIAL DIVERSITY IN URBAN AREAS: ALTERNATIVE MEASURES AND INTERMETROPOLITAN COMPARISONS*

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In his *Preface to Urban Economics,* Wilbur Thompson describes, in terms of industry mix, a system of urban area tradeoffs among income level, income equality, and income stability [9, Chapter 2]. For example, Flint, Michigan, will have a relatively high level of income because of its relatively large fraction of employment in higher paying durable manufacturing industries and a relatively more equal distribution of earnings because of the strong union influence in durable manufacturing industries; but precisely because of the dominance of durable goods industries, it will be subject to a relatively high degree of cyclical instability. The issues of urban income level and urban income equality have received an increasing amount of attention in the still new literature of urban economics, but the stability question-particularly as it relates to diversity in industrial structure-has been largely ignored. The basic purpose of this research is to make interurban comparisons of the industrial diversification dimension of local stability.

Approaches to the measurement of industrial concentration differ in their definition of a "normal" proportion of employment for each industry and in the method of measuring deviations from this norm. Even a cursorv review of the literature, as presented' here, reveals wide variety. An early attempt to compare ordinally the industrial diversity of urban areas was unde1taken by McLaughlin [*4]*. He computed concentration ratios for 14 cities using value added in manufacturing in the five leading industries. Eight years later, Tress [10] approached the problem by computing a diversity index in terms of deviations from an equal percentage distribution (i.e., from 8.3 percent since he used 12 industry classes). Florence [3] measured the industrial balance of states by computing by industry, for each state, absolute deviations from the U.S. average, a relatively high index indicating a correspondingly high degree of specialization. Reinwald [*6]* developed crude comparisons of manufacturing diversity by computing the percent of manufacturing employment in the leading local industries and in the two largest regional industrial groups. Steigenga [8] approached the problem by calculating the variance of the distribution of percent employed across 25 employment classes. By specifying variance as the indicator of diversity, Steigenga is implicitly using national average employment in each industry as a norm from which to compute diversification. Finally, Rodgers [7] examined diversification in manufacturing by developing an ogive on 11 two-digit standard industrial classes. His index is similar to a Cini coefficient.

To date, probably the most sophisticated analysis is the "minimum requirements" technique used by Ullman and Dacey *[11, 12].* They define "normal" employment in each Standard Industrial Classification (SIC) category as that percent which will exactly satisfy local needs. To estimate this percentage, Ullman and Dacey group cities by population size and choose the minimum percent employed for each industry and population size class. These minima are then regressed on population; the resulting equations are used to generate estimates of the minimum requirement by industry for each city. The diversity index (D) as computed by Ullman and Dacey is given by the following formula:

$$D = \frac{\sum_{i=1}^{n} \frac{(P_i - M_i)^2}{M_i}}{\frac{\left(\sum_{i=1}^{n} P_i - \sum_{i=1}^{n} M_i\right)^2}{\sum_{i=1}^{n} M_i}} \quad (1)$$

where,

P_i = percent of employment in the i^{th} industry class,

M_i = minimum requirements percent in the i^{th} industry class,

n = number of industry classes.

Any approach to measuring urban industrial diversity requires definition of the level of aggregation both in terms of observations analyzed and in terms of the industrial classifications employed. In either case, there is no strong scientific basis for choosing a particular level of aggregation, hence whatever assumption is made will open the possibility of a bias in the analysis.

The unit of analysis used should theoretically approximate a self-contained urban economy, and though it does present problems in this regard, the Census Bureau's concept of a Standard Metropolitan Statistical Area (SMSA) is adopted here as the most satisfactory of the available altematives[1]. The empirical analysis to follow utilizes all 212 SMSAs defined at the time of the 1960 Census.

Of greater methodological concern is the specification of a "meaningful" industrial taxonomy. The overall picture of industrial diversity sought here is lost through too detailed a disaggregation, while too great an aggregation would tend to suppress the important variation which exists within certain broad industrial categories, particularly manufacturing. The latter

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[1] No attempt is made here to modify the SMSA format so as to deal more adequately with a major shortcoming-the problem of satellite SMSAs such as Gary or Jersey City.

fault, which produces a distorted image of the relative stability of urban areas, was found with the Ullman-Dacey methodology which employs a 14-industry (SIC one-digit) classification *[12,* pp. 25-29]. For our purposes, a finer disaggregation (than that used by Ullman-Dacey) was felt necessary in order to identify the variation present within broad (SIC one digit) industry classes. Accordingly, the two-digit, 41-industry SIC taxonomy was employed, breaking durable manufacturing into eight classes and nondurable into seven, while further disaggregating the somewhat general SIC one-digit categories. Although this structure suffers from some unbalanced disaggregation – such variously sized economic activities as apparel manufacturing and retail eating and drinking are each given equal weight – there is no a priori evidence that any other weighting of SIC categories will yield more reasonable results.

This greater disaggregation fits our intentions more closely. Since the export sector is the catalyst of urban economic instability, it is desirable to employ an index which reflects the dominance of one or a few specific *industries* rather than one which might emphasize a larger but less relevant industrial *grouping.*

ALTERNATIVE MEASUREMENTS

Previous studies may be classified one of three groups, depending upon their definition of "normal" employment, i.e., ogive, national average, or minimum requirement. This section compares these alternative approaches both conceptually and empirically. A diversity index is calculated by each method for each of the 212 metropolitan areas and is presented in the Appendix.

THE MINIMUM REQUIREMENTS METHOD

In the process of computing a minimum requirements (MR) diversity index, total employment is classified into a basic and a nonbasic sector. In so doing, we employ the general method of Ullman-Dacey [11, pp. 176-84] and Alexandersson [1, pp. 9-26].

First, the 212 SMSAs are grouped into six population size classes. The size classes chosen are those used in the 1960 Census of Population for categorizing SMSAs and do not necessarily reflect homogeneity other than in population size. As will become obvious in the following discussion, the minimum requirements procedure does not give results which are independent of the choice of population size class, but it is not at all apparent that an alternative set of size classes would provide more meaningful results.

For each of these six classes, the percent of total 1960 employment in each of 39 SIC classes (exclusive of total manufacturing and industry not reported) is computed and ranked. The lowest percent in each population size class for each SIC class is identified as the minimum requirements percent.

The minimum percent was plotted against the population of the particular **SMSA** having that minimum. Least squares regression equations of the type

$$M_i = \alpha_i + \beta_i \log(\text{population}) \quad (2)$$
$$i = 1,2 \ldots, 39$$

were fitted to the six points for each industry, except when the minima were invariant with respect to population size.[2] Estimates of individual **SMSA** minimum requirements are obtained by substituting into each industry equation the appropriate population value. The resulting estimates of Mi are summed for each **SMSA** to obtain the estimated fraction of total employment involved in producing goods and services for local consumption. These percentages, the nonbasic sector estimates, are shown in column (5) in the Appendix for each of the 212 SMSAs.

The results of computing the MR diversity index, equation *(1),* based on the M_i are shown in column (2) of the Appendix. Larger index numbers indicate greater specialization, the greatest diversity being described by numbers closer to zero. The results obtained with this method seem to be reasonable on an intuitive basis: the greatest specialization is shown for the heavily industrial areas of Seattle, Pittsburgh, Cleveland, Dayton, Detroit, Flint, Gary, Steubenville, and Youngstown. Alternatively, the greatest employment diversity is indicated for Tampa-St. Petersburg, San Francisco, San Antonio, Portland (Oregon), New York City, Muskegon, Madison, Jackson (Mississippi), Honolulu, Ft. Lauderdale, Denver, Boston, and Austin.

A MODIFIED MINIMUM REQUIREMENTS METHOD

Consider the components of the MR index, equation *(1).* The numerator,

$$\sum \frac{(P_i - M_i)^2}{M_i} \qquad i = 1,2, \ldots, 39 \quad (3)$$

accentuates deviations from the expected minimum percents and accounts for interarea differences in the size of the minimum requirement. For example, a deviation, $(P_i - M_i)2$, of 10 percent is weighted more heavily if the expected minimum is 4 percent than if it is 8 percent. In other words, a 5 percent employment deviation in retail trade, ceteris paribus, does not indicate specialization as strongly as does a 5 percent deviation in motor vehicle manufacturing. The denominator,

[2] When the minimum was statistically invariant with respect to population size, the national metropolitan average was taken to be the minimum percent. These industries (SIC two-digit) were construction, furniture, machinery, other nondurable goods, food and dairy products, and repair services.

$$\frac{(\Sigma P_i - \Sigma M_i)^2}{\Sigma M_i} \qquad i = 1,2, \ldots ,39 \qquad (4)$$

was originally inserted to reconcile the numerator to city size [11, p. 189]. In fact, this value generally will be smaller for large cities (regardless of the nature of their employment diversity) and will, *ceteris paribus,* tend to "blow up" the overall index for larger cities. Since !.Pi equals total employment (100 percent) and $\sum M_i$ equals that percent assigned to the local sector, equation *(4)* indicates the ratio of the percentage assigned to the export sector (squared) to the percentage assigned to the local sector. Because this value relates inversely to population size (if we accept generally held notions of import substitution), a population size bias is inherent in the MR index.

An alternative approach is to eliminate this bias by using only the numerator as an index of industrial diversity (henceforth referred to as the adjusted MR index). The logic here is that the regression method used to estimate Mi adjusts for city size. A comparison of the simple correlation coefficients shows that this adjustment reduces the simple correlation between population and the index of industrial diversification from significantly positive (when the MR method is used) to not significantly different from zero (when the adjusted MR method is used).

The industrial diversification of the 212 SMSAs as measured by this adjusted index is shown in column (1) of the Appendix. These results are similar to that described above except that, as would be expected, larger urban areas will show a greater diversity under the adjusted than under the original index, the reverse being true for smaller urban areas. Moreover, certain of the medium size metropolitan areas show a much greater degree of specialization, e.g., Lewiston, Midland, Muskegon, New Britain, and Wichita. While the adjusted MR approach is unrelated linearly to population size, there is some evidence that a nonlinear, parabolic relationship does exist.

THE OGIVE APPROACH

A third possibility for examining industrial diversity is to treat as abnormal any deviation from a rectangular distribution of employment across industry classes. In our analysis of 39 SIC classes, this would mean 2.56 percent in each SIC class as the norm. The diversity index can then be computed by equation *(3)* with Mi = 2.56 for all i. The results given by this method are shown in column (3) of the Appendix. This may be called an ogive index, since the same ordinal ranking could have been obtained by plotting for each SMSA a relative cumulative frequency distribution of percent employed on number of industries, and by comparing the areas between each Lorenz curve and the main diagonal.

Since the expected norm is the same for each industrial sector, the index will weight heavily the absence of employment in a particular sector regardless of the overall employment distribution.

TABLE 1

SIMPLE CORRELATION COEFFICIENTS AMONG DIVERSITY INDEXES, POPULATION SIZE, AND MEDIAN FAMILY INCOME

	Diversity Indexes				
	MR	*Adjusted MR*	*Ogive*	*National Average*	*Population*
Diversity Indexes					
MR					
Adjusted MR	*.95*				
Ogive	*.36*	*.54*			
National average	*.44*	*.62*	*.85*		
Population	*.14*	*.02*	*--.18*	*--.11*	
Median family income	*.18*	*.15*	*.03*	*.10*	*.28*

Source: Calculated from data in the Appendix.

Thus, the expectation is that the larger urban areas, where there is employment in virtually every manufacturing sector, will show greater diversification. From the Appendix it may be seen that the ogive method shows the six most diversified urban economies to be St. Louis, Philadelphia, Jersey City, Cleveland, Cincinnati, and Chicago. Conversely the six most specialized urban economies are Flint, Gary, Lewiston, Steubenville, Washington, D.C., and Youngstown. Therefore, while the list of those urban areas identified as most diverse does not conform to a priori notions, the ogive index does appear to pick up the extreme cases of industrial specialization.

THE NATIONAL AVERAGE APPROACH

A fourth method of indexing employment specialization is to treat national average employment as the norm, i.e., to let M_i in equation *(3)* be equal to national (urban) average employment in the i^{th} industry. The results of this computation are shown in column (4) of the Appendix. This method differs only slightly from that of computing a variance of the percentage distribution of employment within each SMSA – the difference being the weighting $(1/M_i)$ of the squared deviations.

The national average and ogive indexes should give similar results in that each identify the extreme cases of industrial specialization and each have a bias in favor of larger SMSAs. Examination of the Appendix verifies these common characteristics. Moreover, the simple correlation between these two indexes (0.85) indicates that there is little distinction.

CHOOSING AN APPROPRIATE METHOD

The similarity among the indexes may be described with a matrix of simple correlation coefficients (see Table 1). These coefficients show the two alternative MR methods to give very similar results and the ogive and national average methods to give similar results. The correlation matrix also indicates that a fundamental difference exists in the relationship to population size. Both MR methods tend to indicate greater specialization for larger urban areas whereas the reverse is hue for the national average and ogive approaches.

This duality of the population size dimension is also illustrated by the distribution in Table 2 which shows the broad relationship between each index and population size. In general, the table reveals: (a) the MR approach shows that larger SMSAs have more specialized economies; (b) the adjusted MR approach suggests the possibility of a U-shaped specialization function, i.e.,

TABLE 2

COMPARISON OF DIVERSITY INDEXES BY POPULATION SIZE CLASSES

Population Size Class (In Thousands)	MR	Adjusted MR	Ogive	National Average	Number of SMSAs
	*Indexes**				
50- 99	11.80	21.47	1.39	1.20	23
100-199	10.60	15.97	1.32	.98	67
200-299	11.45	15.25	1.15	.92	41
300-499	15.50	18.31	1.15	1.00	28
500-999	19.46	20.77	1.10	.65	29
Over 1,000	34.02	28.35	0.75	.43	24
Average for 212 SMSAs	15.40	18.79	1.18	.89	

* The figures are averages for the class.
Source: Calculated from data in the Appendix.

that the largest and the smallest SMSAs have the most specialized economies; (c) the ogive approach shows a relatively consistent pattern of larger SMSAs having a more diversified industry structure; and (d) the national average method shows the larger SMSAs to be generally more diversified and the smallest SMSAs to be far more heavily specialized.

Given that these methods produce differing results, the task remains to select the most appropriate measure of industrial diversity. This choice must rest on normative grounds and be guided by the intended use of the measurement. We have already argued that because of its inherent size bias the Ullman-Dacey MR method must be adjusted. Between the ogive and national average methods, the latter may be accepted on grounds that national, urban average employment more closely approximates an industry norm or expected employment than does an equal percentage distribution of 2.56 percent.

Thus, the choice narrows to the national average and adjusted MR indexes. The major difference between the two is that only the latter links industry "norms" to population size. Given the body of literature that suggests employment requirements are related to population size, at least in the local sector, we accept the adjusted minimum requirements method as the most appropriate measure of industrial diversification. Moreover, if the diversity index is to be used to indicate cyclical instability in the urban economy, there is another argument for the preferability of the adjusted MR method. That particular index shows not only the susceptibility of the local economy in the event of the decline of a small number of industries but also the potential for this decline in exports to be transmitted into local sectoral declines (the latter because it permits a dichotomization between basic and nonbasic employment). For example, smaller **SMSAs** may have high fractions of employment in export industries but the second round effects of declines in these industries are limited by the relatively small fraction of employment in service industries. For smaller areas, use of a national average as the norm will average out the anticipated larger export sector and smaller local sector employment. Using this approach, there is no resulting division between basic and nonbasic employment.

THE OPTIMUM-SIZED CITY: A DIGRESSION

The question of what is the optimum-sized city has been dredged up so often and battered around so indiscriminantly that one becomes hesitant to broach the subject again. Thus far, the literature offers only analyses of public expenditure differentials among different sized cities, an exercise not likely to produce fruitful results[3], However, in the present context, there is at least a handle to grasp: is there a particular city size which tends to have the greatest degree of diversification?

To determine whether such a minimum does exist, we hypothesize a parabolic relationship between industrial diversity and population, and obtain a least squares fit

$$D_i = 15.897903 + \underset{(5.65)}{0.008174P} - \underset{(5.97)}{0.000001P^2} \qquad (5)$$

$$R^2 = 0.17$$

where

D_i = adjusted Ullman-Dacey index,
P = population size in thousands.[4]

Though not overwhelming, the fit is statistically significant and suggests that there is a “least

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[3] See, for example, Duncan *[2,* pp. 632-45]. An exception to the use of public expenditure data is given by E. S. Miller [5] who examined optimum size in relation to retail sales activity.

[4] F-ratios for significance tests of regression coefficients are shown in parentheses.

optimal" sized city where industrial specialization at a population of 4,041,000.[5]

The inference here is that there are forces at work which tend to move urban areas toward greater industrial specialization until a certain critical size is reached. If growth may be sustained beyond this size (about 4 million in our analysis), the process is reversed.

CONCLUSIONS AND IMPLICATIONS: AN URBAN-INFERIOR THESIS

The purpose of the preceding analysis is to describe the available alternatives for measuring urban industrial diversity, to evaluate these alternatives, and to use each in computing a diversity index for the 212 SMSAs defined in 1960. It was concluded that a minimum requirements approach yields the most promising results.

The above findings have implications which are potentially important to urban policy as well as being of academic interest.

The minimum requirements approach permits estimation of the percent of nonbasic employment for each urban economy. The results (significantly larger local sectors in larger areas) lends some empirical credence to the argument that population size is associated not only with absolute but also relative increases in tertiary employment. A second finding is equally interesting. Of the 11 industry classes showing a *lower* predicted minimum requirement for larger SMSAs, none are in the service sector and seven are classified as manufacturing industries.[6] Greater requirements for services in large cities (a marginal propensity to import, which declines with population size) is only one possible explanation of the negative coefficients. A second is that certain industries may be (physically) "urban-inferior" in terms of location. As urbanization progresses and land in the metropolitan fringe becomes scarce, the cost of land as a factor of production begins to weigh more heavily in the decision-making process. Such land-extensive activities as farming, mining, and certain forms of manufacturing compete for space with activities that are less dependent upon large inputs of land. Thus, these land-extensive activities become relatively inferior land uses in the urban environment and are increasingly outbid for land by more productive forms of industry. Our results suggest that this "urban-inferior" thesis is generally less applicable in the smaller metropolitan areas (e.g., smaller in population) where there remains a relatively large rural component.

In the case of manufacturing sectors, certain other factors also contribute to this centrifugal movement, though surely the bidding up of urban land values is a major factor. The eight manufacturing sectors which exhibit negative coefficients are generally characterized by a need for space and by input considerations which do not always demand immediate proximity

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[5] From equation (5), $\frac{dI}{dP} = b_1 - 2b_2P$ which is maximized at $P = \frac{b_1}{2b_2}$. The second order conditions are assured since $\frac{d_2I}{dP_2} = 2b_2$ and $b_2 < 0$.

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[6] The 11 are agriculture, forestry, mining, railroad, transportation services, and the manufacturing of primary metals, machinery, electrical machinery, motor vehicle equipment, transportation equipment, textiles, and apparel.

to suppliers. A third contributing factor is the urban planning mechanism whereby industrial parks and heavy industry zoning often encourage exurban location. A fourth consideration is intralocal tax competition-the attempt by outlying communities to bid some industries away from the city and its antitheses, the higher levels of local tax which the core city is forced to levy. No less guilty a culprit is federal highway policy which makes geographically isolated cities increasingly accessible from the point of view of factor inputs. Although each of these factors has been traditionally cited to describe the flight of manufacturing industries to suburban locations, the implication here is that advancing urbanization may push certain secondary activities even further from the SMSA and into the immediate nonmetropolitan hinterland.

Finally, each of these arguments applies as an explanation for the movement of certain industries from larger to smaller SMSAs. A perusal of the list of industries in question reveals the types of blue-collar jobs which are being counted on to bail the cities out of the serious nonwhite unemployment dilemma. However, the pattern of decentralization which we have observed suggests an ever-widening spatial gap between potential place of residence and potential place of work.

If it may be accepted that blue-collar work will increasingly be located not just in suburban areas but beyond the SMSA, the implications for public housing, transportation, and even welfare programs are immense.

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APPENDIX

INDEXES OF DIVERSITY AND MINIMUM REQUIREMENTS EMPLOYMENT, 212 SMSAs: 1960

SMSA Name	*Adjusted Minimum Requirements*	*Minimum Requirements*	*Ogive*	*National Average*	*Minimum Requirement Proportion of Total Employment*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Abilene	11.35	7.00	0.939	0.500	.277
Akron	29.59	25.47	2.331	1.502	.338
Albany, Ga.	12.76	7.30	1.175	0.408	.259
Albany, N.Y.	32.73	32.28	0.705	0.319	.348
Albuquerque	6.10	4.47	1.123	0.892	.310
Allentown	27.91	23.27	0.796	0.913	.336
Altoona	23.66	15.27	1.663	1.905	.284
Amarillo	7.92	5.31	0.914	0.205	.287
Ann Arbor	8.75	5.47	2.003	1.139	.293
Asheville, N.C.	11.64	7.86	0.783	0.643	.282
Atlanta	9.44	10.21	0.655	0.150	.366
Atlantic City	7.02	5.23	1.051	0.536	.290
Augusta	16.21	12.00	1.118	1.161	.302
Austin	4.71	3.61	1.305	0.421	.302
Bakersfield	11.55	8.80	1.474	0.892	.315
Baltimore	16.22	20.23	0.526	0.152	.387
Baton Rouge	8.70	6.35	1.108	0.566	.305
Bay City, Mich.	18.58	13.16	0.987	1.037	.292
Beaumont	18.32	14.50	1.534	0.921	.316
Billings	14.71	8.18	0.991	0.262	.261
Binghamton	21.59	15.45	1.561	1.041	.302
Birmingham	23.17	21.30	1.047	0.595	.346
Boston	2.62	3.61	0.576	0.250	.406
Bridgeport	18.15	15.66	0.715	0.718	.320
Brockton	15.16	10.44	1.140	0.568	.287
Brownsville	11.33	7.58	1.605	0.869	.288
Buffalo	33.76	37.25	0.513	0.308	.376
Canton	25.09	19.98	1.210	0.869	.321
Cedar Rapids	14.80	9.75	1.397	1.086	.284
Champaign-Urbana	8.59	5.53	2.575	1.190	.282
Charleston, S.C.	14.35	10.41	0.969	0.720	.302
Charleston, W. Va.	22.08	17.46	1.493	2.220	.309
Charlotte	7.18	5.81	0.745	0.316	.312
Chattanooga	13.07	10.49	0.728	0.660	.313
Chicago	0.95	1.71	0.487	0.208	.439
Cincinnati	10.12	11.54	0.359	0.148	.368
Cleveland	116.56	140.01	0.482	0.283	.389
Colorado Springs	6.77	4.48	1.033	0.268	.286
Columbia, S.C.	6.19	5.08	0.862	0.274	.310
Columbus, Ga.	20.70	15.35	1.581	1.515	.303
Columbus, Ohio	12.42	11.96	0.583	0.122	.349
Corpus Christi	7.00	5.55	0.763	0.250	.303
Dallas	6.98	7.64	0.628	0.149	.368
Davenport	18.37	13.65	1.276	0.819	.311
Dayton	60.12	58.42	0.987	0.570	.350
Decatur	10.29	6.65	0.823	0.321	.278
Denver	3.15	3.23	0.700	0.135	.362
Des Moines	5.51	4.15	0.921	0.282	.311
Detroit	76.43	109.05	1.577	2.091	.419
Dubuque	14.77	8.35	1.124	0.792	.262
Duluth-Superior	21.82	16.43	1.080	1.756	.312
Durham	14.56	9.25	1.205	0.892	.275
El Paso	6.49	5.13	0.959	0.224	.318
Erie	13.10	10.16	0.622	0.410	.308

Eugene	36.25	23.09	2.489	4.928	.291
Evansville	7.71	5.82	0.590	0.201	.299
Fall River	37.03	24.10	2.244	3.696	.284
Fargo-Moorhead	12.55	7.20	1.426	0.567	.273
Fitchburg	33.78	19.43	2.034	1.408	.263
Flint	166.04	133.50	6.814	10.860	.325
Ft. Lauderdale	4.82	3.91	0.969	0.326	.320
Ft. Smith, Ark.	20.79	11.83	0.927	0.407	.254
Ft. Wayne	12.14	9.88	0.875	0.605	.305
Ft. Worth	29.35	27.92	0.930	0.761	.342
Fresno	10.59	8.76	1.653	0.853	.324
Gadsden	24.76	14.97	1.570	1.039	.270
Galveston	11.28	7.85	0.863	0.946	.285
Gary	92.11	84.28	3.125	2.887	.342
Grand Rapids	9.16	7.25	0.619	0.472	.323
Great Falls	14.82	8.06	0.936	0.249	.258
Green Bay	13.31	8.56	1.027	0.408	.280
Greensboro	24.37	18.21	1.283	1.658	.308
Greenville	39.83	28.55	2.126	3.213	.301
Hamilton	16.74	11.76	0.959	0.597	.299
Harrisburg	7.47	5.90	1.329	0.411	.321
Hartford	34.48	30.24	1.331	1.190	.339
Honolulu	4.21	3.66	1.051	0.426	.337
Houston	6.11	7.11	0.567	0.186	.374
Huntington	13.35	10.61	0.796	0.450	.309
Huntsville	38.72	23.62	2.185	1.945	.277
Indiana	25.65	25.89	0.601	0.202	.350
Jackson, Mich.	14.08	9.30	0.800	0.795	.282
Jackson, Miss.	5.20	3.59	0.787	0.272	.296
Jacksonville	4.46	4.12	0.893	0.227	.323
Jersey City	18.65	17.69	0.454	0.500	.345
Johnstown	36.32	26.69	1.648	1.730	.313
Kalamazoo	14.32	9.92	1.055	0.610	.292
Kansas City	5.63	6.45	0.582	0.313	.366
Kenosha	35.52	22.30	2.255	3.526	.271
Knoxville	12.53	10.50	0.796	0.725	.324
Lake Charles	12.20	8.04	0.945	0.578	.286
Lancaster	9.96	7.73	0.701	0.535	.313
Lansing	23.89	18.45	1.604	1.558	.316
Laredo	23.65	11.63	1.469	0.439	.253
Las Vegas	8.05	5.57	2.174	1.839	.281
Lawrence	22.13	15.72	1.589	1.252	.297
Lawton	11.57	7.36	1.272	0.293	.267
Lewiston	42.59	22.97	3.099	3.164	.256
Lexington	8.21	5.47	0.914	0.223	.282
Lima	12.03	7.33	0.636	0.435	.272
Lincoln	7.08	4.59	0.949	0.246	.289
Little Rock	5.24	4.01	0.733	0.210	.307
Lorain-Elyria	28.65	20.62	1.351	1.460	.303
Los Angeles	4.40	7.60	0.502	0.301	.443
Louisville	30.60	30.99	0.514	0.159	.352
Lowell	11.77	8.69	0.773	0.669	.289
Lubbock	8.57	5.64	1.127	0.308	.289
Lynchburg	10.88	6.56	0.590	0.429	.275
Macon	7.41	5.11	1.958	0.679	.295
Madison	5.37	3.78	1.168	0.395	.303
Manchester	23.34	14.20	1.669	1.408	.269
Memphis	4.88	4.59	0.768	0.203	.345
Meriden	32.26	14.85	1.463	1.705	.244
Miami	3.65	4.23	0.875	0.481	.362
Midland	45.05	22.18	2.440	5.654	.255
Milwaukee	7.94	8.61	0.713	0.430	.372
Minneapolis-St. Paul	4.14	4.73	0.640	0.192	.381

Mobile	6.94	5.46	1.378	0.500	.318
Monroe	11.76	6.98	1.001	0.338	.271
Montgomery	6.82	4.99	1.281	0.429	.291
Muncie	15.54	21.48	1.051	1.062	.275
Muskegon	32.71	3.51	2.072	1.711	.287
Nashville	4.23	14.21	0.584	0.178	.327
New Bedford	20.89	24.72	1.171	1.835	.285
New Britain	39.07	24.72	2.379	2.166	.281
New Haven	7.16	5.89	0.509	0.333	.317
New London	23.52	16.98	1.142	1.437	.289
New Orleans	4.63	4.95	0.674	0.353	.359
New York	1.67	3.39	0.562	0.414	.462
Newark	7.21	9.26	0.502	0.312	.386
Newport	41.03	30.07	2.324	2.586	.304
Norfolk	13.31	12.11	1.299	0.520	.342
Norwalk	9.64	6.64	0.523	0.463	.269
Odessa	26.95	15.41	1.554	2.779	.267
Ogden	11.50	6.98	2.696	1.188	.275
Oklahoma City	4.31	4.20	1.203	0.292	.337
Omaha	5.69	4.94	0.823	0.374	.333
Orlando	6.30	5.07	0.981	0.363	.318
Paterson	29.21	31.39	0.416	0.289	.372
Pensacola	10.62	7.48	1.281	0.632	.300
Peoria	25.99	20.48	1.977	1.414	.314
Philadelphia	4.66	7.07	0.379	0.127	.425
Phoenix	7.12	7.22	0.778	0.212	.348
Pittsburgh	158.30	198.70	1.204	0.926	.401
Pittsfield	21.81	12.53	2.043	2.074	.258
Portland, Me.	10.16	6.83	0.945	0.257	.278
Portland, Oregon	3.43	3.33	0.546	0.144	.357
Providence	21.48	22.52	0.885	0.910	.357
Provo	27.78	17.43	1.906	1.708	.274
Pueblo	32.46	19.41	2.040	1.613	.278
Racine	34.37	15.82	1.060	0.906	.235
Raleigh	5.78	4.15	0.969	0.277	.292
Reading	15.27	11.57	0.580	0.589	.312
Reno	13.14	7.39	1.141	1.598	.264
Richmond	6.88	7.00	0.840	0.230	.328
Roanoke	9.65	6.53	0.760	0.415	.290
Rochester	16.67	15.37	1.529	1.710	.343
Rockford	22.10	15.80	1.521	1.223	.301
Sacramento	4.67	4.04	1.802	0.657	.337
Saginaw	22.39	14.91	1.187	1.231	.297
St. Joseph	11.81	7.31	1.341	0.666	.267
St. Louis	7.87	10.35	0.383	0.103	.394
Salt Lake City	6.72	5.56	0.731	0.291	.326
San Angelo	16.85	9.05	0.915	0.262	.253
San Antonio	4.04	3.90	1.501	0.372	.350
San Bernardino	6.40	6.15	0.841	0.229	.356
San Diego	28.76	30.20	1.107	0.640	.366
San Francisco	2.03	2.84	0.583	0.158	.407
San Jose	18.37	17.45	0.711	0.398	.347
Santa Barbara	6.45	4.83	0.776	0.230	.292
Savannah	9.12	6.46	0.909	0.390	.297
Scranton	14.80	11.19	0.717	0.927	.306
Seattle	136.25	143.26	1.025	1.119	.369
Shreveport	6.16	4.80	0.841	0.374	.313
Sioux City	10.57	6.87	1.206	0.445	.274
Sioux Falls	11.66	6.67	1.294	0.617	.265
South Bend	22.40	16.54	1.066	1.233	.304
Spokane	6.50	4.80	0.824	0.193	.313
Springfield, Ill.	7.24	4.92	1.021	0.309	.286
Springfield, Mo.	10.02	6.46	0.811	0.188	.280

Springfield, Ohio	12.27	8.16	0.960	0.556	.282
Springfield, Mass.	9.09	8.09	0.556	0.239	.335
Stamford	7.08	5.45	0.614	0.442	.294
Steubenville	90.65	60.50	5.143	4.976	.292
Stockton	7.73	6.62	1.226	0.561	.308
Syracuse	17.95	16.55	0.569	0.289	.341
Tacoma	7.17	5.61	0.787	0.366	.319
Tampa-St. Petersburg	0.06	0.07	0.806	0.133	.354
Terre Haute	9.06	6.24	0.690	0.203	.274
Texarkana	20.37	11.86	1.081	0.528	.267
Toledo	10.63	9.23	0.552	0.351	.333
Topeka	8.83	6.07	1.077	0.491	.285
Trenton	6.58	5.12	0.590	0.280	.311
Tucson	6.83	5.25	0.909	0.358	.311
Tulsa	9.12	8.08	0.623	0.463	.329
Tuscaloosa	11.51	6.86	1.110	0.496	.274
Tyler	12.36	7.41	0.809	0.339	.265
Utica-Rome	8.29	6.75	0.671	0.218	.320
Waco	7.97	5.14	0.801	0.209	.287
Washington	3.08	4.11	3.025	1.158	.393
Waterbury	18.76	12.97	1.232	1.123	.295
Waterloo	17.16	10.37	1.711	1.040	.279
West Palm Beach	9.66	7.24	1.490	0.810	.304
Wheeling	14.74	10.31	0.808	0.610	.295
Wichita	57.71	47.17	1.997	2.678	.321
Wichita Falls	14.33	9.24	1.062	0.830	.281
Wilkes-Barre	20.62	18.84	0.867	1.210	.322
Wilmington	23.00	20.06	1.364	2.168	.324
Winston-Salem	22.16	15.96	1.530	1.334	.297
Worcester	11.94	9.30	0.727	0.423	.319
York	12.04	8.54	0.712	0.493	.306
Youngstown	75.06	64.94	2.714	2.423	.337

Source: Urban Economics Data Bank, Syracuse University.