Metropolitan Wage Differentials: Can Cleveland Still Compete?

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Introduction

Labor costs are often cited as one of the primary reasons for the economic hardships plaguing many older industrial cities, such as Cleveland. Of course, other factors, such as local taxes, proximity to markets, product cycles, and energy costs may also contribute to the area's diminished ability to compete with other regions in attracting and retaining businesses. Nonetheless, since labor costs represent an important part of total production costs, the initial presence of significant wage differentials among metropolitan areas may have been a major factor in the economic expansion of Sunbelt cities and the relative decline of Snowbelt cities. In turn, divergent patterns of growth resulting partly from firms relocating in low-wage areas may have caused wage levels to converge.

With respect to the effect of differential labor costs on firm location and on regional employment growth, two aspects of labor costs must be considered. First, there is more to examining labor cost differentials across regions than simply looking at regional differences in wage rates. Firms consider not only the amount they pay workers, but also the productivity of their workers. Stated simply, an employer is willing to pay a worker in Cleveland a higher hourly wage than a worker in Atlanta, for example, if the Cleveland worker is more productive than the Atlanta worker. Therefore, a comparison of regional wage differentials is much more meaningful when these wages are adjusted for differences in worker skills.

Second, the advantage to a firm in searching for a low-wage area is directly proportional to the degree of regional dispersion in labor costs. A large regional variation in labor costs would make it advantageous for firms to search for low-wage areas, since the relative cost savings would be sizable. On the other hand, if wage differentials, adjusted for worker skills, are observed to converge over time, then the competitive disadvantage of relatively high-wage areas, such as Cleveland, would diminish over time.

The purpose of this paper is threefold: to provide estimates of variations across metropolitan areas in the wage employers pay a worker of given skills and training, to compare these "skill-adjusted wage differentials with observed differentials,and to examine how these differentials may have changed over the past decade. The Cleveland metropolitan labor market is used as a point of comparison to highlight how labor costs in a major industrial city in the Fourth Federal Reserve District fare with respect to other U. S. cities.

I. Theoretical Framework

Metropolitan areas in the United States are characterized by many firms that act as price-takers when they sell to national markets and that consider the rental prices of capital to be fixed by external conditions (see Borts and Stein [1964]; and Muth [1968 and 1983]). This demand-side interpretation of regional labor markets fixes local nominal wages by the horizontal labor demand curve of firms competing in national or international product markets. Long-run equilibrium levels of local wages are determined by the demand for labor, under the technical condition that the level of output changes in constant proportion to changes in labor and capital. Shifts in labor supply have no long-run effect on local nominal wages in this model, but supply changes do cause changes in total employment and eventually in total population. Of course, other influences on local wages are possible in short-run disequilibrium and even in long-run equilibrium, if local products are relatively unique or sold in geographically limited markets, if local natural resources are a significant input into the production of exportable goods, or if any of the other conditions of the demand-side model above are violated. Johnson (1983) provides an extensive theoretical and empirical analysis of many of these factors, including local costs of living, environmental amenities important to workers, taxes, income transfers, moving costs, unionization, transportation costs, discrimination, and various human capital and skill variables. Most of the previous studies of geographical wage differentials have allowed a dominant role for labor supply in determining local wages (see Coelho and Ghali [1971]; Bellante [1979]; Sahling and Smith [1983]; Scully [1969]; and Johnson [1983]).

Estimates of Wage Equations for 1974 and 1983
(*Current* Population ***Survey*** data)

Variable	1974	1983
Intercept	1.26	1.58
	(39.08)	(115.27)
Schooling	0.12	0.13
	(9.15)	(30.70)
Schooling squared	0.007	0.004
	(2.17)	(3.18)
Potential experience	0.024	0.026
	(31.39)	(114.22)
Potential experience squared	-0.0004	-0.0004
	(-25.05)	(-86.03)
Employment status (full-time = 1)	0.14	0.16
	(14.25)	(58.34)
Gender (female = 1)	-0.31	-0.23
	(-35.15)	(-96.52)
Race (nonwhite = 1)	-0.05	-0.02
	(-3.90)	(-6.82)
Occupation dummy variables (omitted for brevity)	————	————
R-square	0.49	0.49
Number of observations	13,733	175,268

NOTES: Coefficients are followed by t-statistics in parentheses. The 1983 regression also contains quarterly dummy variables to control for variations during 1983. See text for definition of variables and further explanation of data. All coefficients are statistically significant at the 0.01 percent level, except for schooling squared in 1974, which is statistically significant at the 0.05 percent level.

TABLE 1

Without necessarily denying a role for nondemand factors, the purpose of our study is to obtain estimates of metropolitan wage differentials relevant for identifying demand-side effects and to explore the possible significance of such effects over the past decade. To do this, we first estimate the demand-side differentials for 1974 and 1983, and then examine the trends in the differentials between the two periods. Under the demand-side model, the change in skill-adjusted wage differentials during this period is expected (all else the same) to be inversely related to subsequent rates of economic growth via firm locations, expansions, and contractions. We have found in Eberts and Stone (1985), for example, a significant inverse relationship between metropolitan wage differentials in the 1970s and subsequent firm locations. Therefore, one would expect wage differentials measured in 1974 to narrow by 1983.

II. Data and Empirical Results

The data used to estimate the metropolitan wage differentials are obtained from 1974 and 1983 ***Current Population Surveys*** (CPS) compiled by the Bureau of Labor Statistics. The 1974 data come from the May survey, which contains supplementary questions regarding employment. The 1983 information is derived from questions asked of one-quarter of the individuals in each of the 12 monthly surveys. Because of this difference (and also because of other changes in the CPS between 1974 and 1983), the total number of workers with sufficiently complete records for analysis is much smaller in 1974 than in 1983 (13,733 workers in 1974 versus 175,268 in 1983). The sample allows us to identify 43 of the largest metropolitan areas—Standard Metropolitan Statistical Areas (SMSAs)—for both years of data.

Our first step in obtaining skill-adjusted wage differentials is to specify estimable wage equations that reflect appropriate demand determinants of the wages of individual workers. This approach follows the human capital specification of individual wages set forth by Hanoch (1967) and Mincer (1974). Thus, we specify individual wages (expressed in logarithms) as a function of observed determinants of individual productivity—education level (entered as a quadratic), potential experience (age, minus years of education, minus six, also entered as a quadratic), a binary dummy variable indicating full-time employment status, and 46 binary occupation dummy variables (with one of these omitted as a constant). Binary dummy variables are also entered to control for race and gender differences in wages. Under the assumptions of the demand model, the separate wage regressions for 1974 and 1983 yield coefficients that reflect national average marginal productivities in specific occupations and for particular human capital components. Industry dummy variables and union membership status are not included, because these variables are not viewed as productive attributes. Detailed information on other components of labor compensation (pensions, health insurance, and the like) is not available in the data.

The predicted wage level for each worker in the sample is obtained by multiplying the estimated coefficients by each worker's characteristics. The predicted wage can be interpreted as the compensation a worker could expect to receive, given his or her characteristics, regardless of geographic location. Subtracting the predicted wage from the actual wage, then, nets out the portion of the actual wage that is related to the worker's skills. The skill-adjusted metropolitan wage differentials are then obtained by averaging the wage residuals (actual, minus predicted wage) in each year for all workers in a particular metropolitan area. Average wage differentials are calculated for each of the 43 SMSAs for each year. The national average wage differential is, of course, equal to zero by the property of least-squares regression. For purposes of comparison, an additional average is calculated jointly for nonSMSAs and other excluded SMSAs.

1974 Metropolitan Wage Differentials (percentage difference from national average)

Rank	SMSA	Skill-adjusted	Actual
1	New York	18.6	21.6
2	Paterson	17.9	18.6
3	San Francisco	17.5	19.8
4	Detroit	17.1	23.6
5	Chicago	15.7	16.1
6	Nassau-Suffolk	15.5	24.8
7	Rochester	14.5	19.9
8	San Jose	13.4	23.7
9	Portland	13.3	16.8
10	Gary	12.9	10.5
11	San Diego	12.9	21.2
12	Anaheim	12.2	27.3
13	Seattle	9.1	24.4
14	Los Angeles	8.4	10.8
15	Albany	8.3	18.7
16	Akron	7.9	3.8
17	Cleveland	7.5	14.4
18	Atlanta	6.5	2.8
19	Denver	5.9	11.4
20	New Orleans	5.9	-0.8
21	Baltimore	5.8	5.4
22	Sacramento	5.7	9.0
23	Indianapolis	5.5	8.9
24	Minneapolis-St. Paul	5.1	9.8
25	Milwaukee	4.9	8.0
26	Columbus	4.3	3.9
27	Boston	4.1	9.4
28	San Bemardino	3.9	5.0
29	Houston	3.8	10.4
30	Newark	3.7	3.6
31	Philadelphia	3.1	6.3
32	St. Louis	1.4	1.7
33	Pittsburgh	0.6	-1.6
34	Cincinnati	0.5	-0.3
35	Miami	-0.6	0.2
36	Kansas City	-1.8	3.6
37	Dallas	-2.9	-0.9
38	Ft. Worth	-4.4	-0.5
39	Birmingham	-4.7	0.1
40	NonSMSAs and other SMSAs	-5.8	-8.7
41	Buffalo	-6.9	-4.9
42	Norfolk	-7.1	-7.6
43	Greensboro	-8.1	-8.6
44	Tampa	-15.9	-17.9

NOTE: **Wage differentials are derived from** *Current Population Survey* **files, using the technique described in the text.**

TABLE 2

Wage regressions. The estimated (log) wage equations for both 1974 and 1983 are presented in *table 1*, except that the 45 estimated coefficients for the occupation dummy variables are omitted for brevity. These equations are presented only to document the results of our demand-oriented wage regressions. Except for the absence of nondemand factors (for example, controls for union membership), these are familiar regressions (with minor variations) in the labor literature.

The estimated coefficients in *table 1* are as expected in both years. Schooling (with a value equal to 1 for eight to 11 years, a value of 2 for 12 to 15 years, a value of 3 for 16 to 17 years, and a value of 4 for more than 18 years) enters with a significantly positive coefficient.[1] Schooling squared also enters with a significantly positive coefficient; years of potential experience

1 This specification of education permits greater nonlinearity in the effects of different education levels than the use of individual years of education, although the difference is trivial for our estimated wage differentials.

enters with a positive coefficient; experience squared enters with a negative coefficient; a dummy variable for full-time employment enters with a positive coefficient; and dummy variables for race (with nonwhite equal to 1) and gender (with female equal to 1) enter with negative coefficients. All listed coefficients are significant at the 5 percent level.

With the exception of the decline in absolute value for the race and gender coefficients in 1983, the 1974 and 1983 regressions are basically the same. The similarity extends, by and large, to the 45 occupation dummy variables as well, although a few of these coefficients do change. Intercepts in the two equations, of course, differ significantly, due to both nominal and real wage growth between 1974 and 1983 for the United States as a whole. Both regressions explain 49 percent of the variation in actual wages.

1983 Metropolitan Wage Differentials
(percentage difference from national average)

Rank	SMSA	Skill-adjusted	Actual
1	San Francisco	18.1	25.4
2	San Jose	18.1	28.4
3	Anaheim	15.5	23.0
4	Seattle	14.9	22.1
5	Minneapolis-St. Paul	12.0	12.6
6	Nassau-Suffolk	11.3	16.0
7	Houston	10.8	14.5
8	Los Angeles	10.7	13.0
9	Chicago	10.4	14.5
10	San Bemardino	10.0	7.1
11	Detroit	9.3	9.1
12	Gary	8.4	3.6
13	Dallas	8.0	12.2
14	Portland	7.9	9.7
15	Paterson	7.8	13.5
16	Sacramento	7.8	7.0
17	Denver	7.6	12.7
18	Newark	7.3	12.7
19	Milwaukee	7.1	7.9
20	New York	7.1	11.4
21	San Diego	5.7	4.5
22	Cleveland	5.1	7.0
23	Rochester	5.1	11.0
24	New Orleans	4.8	8.8
25	St. Louis	3.9	4.0
26	Ft. Worth	3.4	3.0
27	Pittsburgh	2.7	5.4
28	Atlanta	2.7	6.2
29	Boston	2.2	5.7
30	Kansas City	2.1	4.5
31	Baltimore	1.6	4.8
32	Philadelphia	1.5	4.7
33	Cincinnati	1.3	1.4
34	Akron	-1.3	1.4
35	Greensboro	-1.6	-3.5
36	Columbus	-2.2	-2.1
37	Indianapolis	-2.5	-2.6
38	Buffalo	-2.6	-4.5
39	NonSMSAs and other SMSAs	-4.8	-7.1
40	Albany	-6.0	-5.4
41	Birmingham	-6.9	-5.1
42	Miami	-6.9	-11.4
43	Norfolk	-7.3	-7.3
44	Tampa	-10.7	-11.7

NOTE: Wage differentials are derived from *Current Population Survey* files, using the technique described in the text.

TABLE 3

Metropolitan wage differentials. Skill-adjusted and actual metropolitan wage differentials (expressed as the percentage deviation from the national average) are presented in ***table*** 2 for 1974 and in ***table*** 3 for 1983. The SMSAs are ranked according to the size of the skill-adjusted differential. Because of the semilogarithmic specification of the wage equation, residuals are exponentiated to obtain percentage differentials.

The rankings offer a perspective on how Cleveland's wages compare with regions against which the area might compete for economic development. In 1974, Cleveland's skill-adjusted wage was 7.5 percent above the national average, which put Cleveland in seventeenth place among the cities considered. A number of cities usually associated with rapid growth, such as San Jose, San Diego, and Anaheim, had wage differentials that were higher than Cleveland's. On the other hand, Cleveland's skill-adjusted wages are consistently higher than they are in southeastern cities. About one-quarter of the cities with wage rates below Cleveland's level were in the Southeast, and no southeastern city had a skill-adjusted wage differential higher than Cleveland's. More-' over, small SMSAs and nonSMSA regions showed much lower skill-adjusted wage differentials than Cleveland's—over 12 percent lower.

In 1983, Cleveland's skill-adjusted wage fell to only slightly above 5 percent of the national average, which brought its ranking down to twenty-second place. All the southern cities in the sample still had wage differentials below Cleveland's. A few additional cities, such as San Bemardino and Sacramento, were added to the 1974 list of west coast cities that surpassed Cleveland in the skill-adjusted wage differential.

Wage differences between metropolitan areas can be broken down into two components: differences in the skill-adjusted wages and differences in the value of skills (measured in dollars). Consider the difference in actual wages between two SMSAs (w_1 and w_o). Recall that:

$$(1)\quad \log(w_o) = bS_o + e_o,$$
$$\log(w_1) = bS_1 + e_1,$$

where b is the regression coefficient associated with the skill-related variables (S), and e denotes the residual or skill-adjusted wages (actual wage, minus predicted wage). We assume that the appropriate aggregation has been done, so that each equation represents wages in a specific metropolitan area.

The difference in the actual (log) wages between the two metropolitan areas is:

$$(2)\quad \log(w_1) - \log(w_o) = b(S_1 - S_o) + (e_1 - e_o)$$

The first component on the right-hand side is the difference in levels of skills normalized in wage units between the two areas. The second is the difference in skill-adjusted wages between the two metropolitan areas. If, for example, the actual wage differential is greater than the skill-adjusted differential, then the skill level is necessarily greater in area *1* than in area o. Consider the wage differentials displayed for San Francisco in *1983*. The actual wage in San Francisco is *17.2* percent higher than the actual wage in Cleveland, but the skill-adjusted wage is only *12.4* percent higher.[2] The difference of *4.8* percentage points is due to the higher skill levels of San Francisco workers relative to Cleveland workers. Since employers are willing to pay workers the value of their contribution to the production of each unit of output, the higher wages associated with higher productivity do not affect the relative competitiveness of the two areas. Rather, it is the difference in wages over and above the differential associated with higher labor productivity that affects competitiveness among regions. In the case of San Francisco, a *12.4* percent wage differential exists, which is not accounted for by skill differentials. On the other hand, Rochester's *3.2* percent wage differential relative to Cleveland is due entirely to higher skill levels in Rochester.

Although the results for *1974* show a rough correspondence between skill-adjusted and observed (actual) wage differentials, substantial differences are also clearly evident. Detroit, Anaheim, Birmingham, San Diego, Cleveland, Houston, and Boston, for example, all have observed wage differentials that exceed the skill-adjusted differential by at least *8* percentage points, which is the approximate differential required for statistical significance at the 5 percent level. Only Akron exhibits the opposite phenomenon—a skill-adjusted differential that is at least *8* percentage points higher than the observed differential. The five SMSAs with the highest skill-adjusted wages are New York, Paterson, San Francisco, Detroit, and Chicago. The five lowest SMSAs are Tampa, Ft. Worth, Greensboro, Norfolk, and Buffalo.

The results for *1983* show a stronger correspondence between skill-adjusted and observed wage differentials. By this year, no SMSA except San Jose has an observed wage differential that differs from the skill-adjusted differential by at least 8 percentage points. Only one of the five highest-wage SMSAs in *1974* (San Francisco) remains in the top five in *1983*. The remaining four in *1983* are San Jose, Anaheim, Seattle, and Minneapolis-St. Paul. Two of the lowest-wage SMSAs in *1974* (Tampa and Norfolk) remain among the five lowest SMSAs in *1983*. The remaining three in *1983* are Albany, Birmingham, and Miami.

The changes in the differentials between *1974* and *1983* are presented in table 4. SMSAs with the largest increases are Dallas, Ft. Worth, Houston, Minneapolis-St. Paul, and Greensboro. SMSAs with the largest decreases are Albany, New York, Paterson, Rochester, and Akron. Most of the cities associated with rapid growth during the last decade exhibit increases in both skill-adjusted and observed wage differentials. In some instances, the skill-adjusted and actual changes in wage differentials differ substantially. SMSAs that show increases in the skill-adjusted differential, but a decline in the actual wage differentials, are Houston, Anaheim, and Sacramento. For these SMSAs, the skill-adjusted increase is presumably offset by a decline in average skill level.

Cleveland's skill-adjusted and observed wage differentials fell between *1974* and *1983;* the actual wage declined more rapidly than the skill-adjusted wage. Since the relative decline in the actual wage differential, with respect to the skill-adjusted wage differential, has to be offset by a decline in average skill level of the area's work force, this indicates that Cleveland suffered a decline in the average skill of the area's labor force.

New Orleans, Philadelphia (trivially), Atlanta, and Akron show decreases in the skill-adjusted wage differential, but an increase in

2 The percentage difference in wages between any two metropolitan areas can be easily calculated from *tables 1* and *2*, by using the following formula:

$$\frac{w_1 - w_0}{w_0} = \left(\frac{w_1 - w_{US}}{w_{US}} - \frac{w_0 - w_{US}}{w_{US}}\right) \quad (1/(1+(w_0 - w_{US})/w_{US}))$$

where $(w_1 - w_0)/w_0$ is the percentage difference in wages between area *1* and area o and $(w_i - w_{US})/w_{US}$ is the percentage deviation in wages in area *i* from the nation's (the differential displayed in tables 2 and 3).

the actual wage differential. For these SMSAs, the skill-adjusted decrease is presumably offset by an increase in the average skill level. Large divergences between the skill-adjusted and actual changes (even if the changes are in the same direction) have similar interpretation. Other SMSAs with large differences between the two measures are San Jose, Birmingham, Gary, San Diego, Detroit, and Albany.

Based on the estimates above, have skill-adjusted metropolitan wage differentials converged since 1974? This question can be answered by calculating the change in the coefficient of variation from *1974* to *1983*. The coefficient of variation is the standard deviation (computed from the sample of SMSA-level wage differentials) divided by the mean; thus, it is an index of the degree of dispersion in the sample. This measure indicates substantial convergence for both sets of differentials, declining by *22* percent for the skill-adjusted differentials and by *46* percent for the actual wage differentials. Because the observed wage differential is composed of the skill-adjusted wage differentia! and a differential related to differences in actual skills, the fact that observed wages converged more than twice as much as skill-adjusted wages suggests that variations across metropolitan areas in actual skill levels also declined during the period.3

Why do we observe relatively strong wage convergence during the 1974-1983 period? Following our demand-side approach, one could attribute convergence to the expanding scope of most product markets (both domestically and internationally), increased competition faced by geographically concentrated firms that may have had some power to influence price, the relative decline of industries that make products using relatively large amounts of local natural resources, and the emergence of manufacturing industries that require smaller-scale plants.

III. Conclusion

The objective of this paper was to provide estimates of variations across metropolitan areas in the wage employers pay a worker of given skills and training, and then to compare how these differentials have changed over the past decade. Based upon *1974* and *1983* data from the ***Current Population Survey,*** we find substantial variations in skill-adjusted wages in both *1974* and *1983,* as well as significant deviations between skill-adjusted and observed wage levels. We also find that the wage differentials and skill differentials converged significantly during this same period. Cleveland's skill-adjusted and actual wage levels

Change in Wage **Differentials from** 1974 to 1983
(percentage point change)

Rank	SMSA	Skill-adjusted	Actual
1	Dallas	10.9	13.1
2	Ft. Worth	7.8	3.5
3	Houston	7.0	4.1
4	Minneapolis-St. Paul	6.9	6.9
5	Greensboro	6.5	5.1
6	San Bernardino	6.1	2.1
7	Seattle	5.8	-2.3
8	Tampa	5.2	6.2
9	San Jose	4.7	6.2
10	Buffalo	4.3	0.4
11	Kansas City	3.9	0.9
12	Newark	3.6	-9.1
13	Anaheim	3.3	-4.3
14	St. Louis	2.5	2.3
15	Los Angeles	2.3	2.2
16	Milwaukee	2.2	-0.1
17	Pittsburgh	2.1	7.0
18	Sacramento	2.1	-2.0
19	Denver	1.7	0.7
20	NonSMSAs and other SMSAs	1.0	1.6
21	Cincinnati	0.8	1.7
22	San Francisco	0.6	5.6
23	Norfolk	-0.2	0.3
24	New Orleans	-1.1	9.6
25	Philadelphia	-1.6	-1.6
26	Boston	-1.9	-3.7
27	Birmingham	*-2.2*	*-5.2*
28	Cleveland	-2.4	-7.4
29	Atlanta	-3.8	3.4
30	Nassau-Suffolk	-4.2	-8.8
31	Baltimore	-4.2	-0.6
32	Gary	-4.5	-6.9
33	Chicago	-5.3	-1.6
34	Portland	-5.4	-7.1
35	Miami	-6.3	-11.6
36	Columbus	-6.5	-6.0
37	San Diego	-7.2	-16.7
38	Detroit	-7.8	-14.5
39	Indianapolis	-8.0	-11.5
40	Akron	-9.2	-2.4
41	Rochester	-9.4	-8.9
42	Paterson	10.1	-5.1
43	New York	-11.5	-10.2
44	Albany	-14.3	-24.1

NOTE: Wage differentials are derived from ***Current Population Survey*** files, using the technique described in the text.

TABLE **4**

3 The change in average skill level could be the result of changes in actual skills or of changes in the market compensation of the skills between 1974 and 1983. The oeneral similaritv of the 1974 and 1983 wage regressions, however, suggests that most ot ihe change in skill level reflects actual changes in skills.

also converged toward the national averages. Over the last decade, Cleveland closed the gap by 2.4 percentage points for skill-adjusted wages and by nearly 9 percentage points for actual wages.

The reduction in Cleveland's wage differentials and the general convergence in wages and skills could influence Cleveland's economic future in at least two ways. First, the incentive for firms to move out of Cleveland might diminish, since convergence in wages reduces the potential cost savings of a move. Second, the wage differential might not be as critical a factor in economic growth as it once was. In fact, labor supply-side factors, such as labor climate and local amenities and public services, might become more important influences on economic development.

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