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Industrial Specialization and the Returns to Labor

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Comparative advantage and the division of labor make geographic concentration of production within a nation profitable and cause many cities to be specialized in one or a few main industries. Specialized cities, however, suffer greater unemployment risk. The theory of compensating wage differentials predicts that individuals living in more specialized cities will be compensated in the form of higher wage rates. We study the effects of specialization on wages and unemployment in the United States. We find evidence of compensating wage differentials. That firms choose to locate in more specialized, higher-wage cities is indirect evidence of the gains to specialization.

I. Introduction

The benefits of industrial specialization and trade are well known. The forces of comparative advantage and the division of labor that make spe-

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cialization among nations profitable often result in geographic concentration of economic activity within a nation. Geographic concentration of production within a nation often entails the specialization of regions in one or a few main industries. There is evidence that industrially specialized regions suffer less stable employment and earnings and higher rates of unemployment on average.[1] An important question is the extent to which the benefits of specialization are offset by this cost.

In the long run, individuals must be compensated for above-average risks of unemployment. Recent empirical work by Topel (1984) and Li (1986), for example, provide empirical support for the compensating differences hypothesis. If this is generally the case, higher wages should offset the higher risk of unemployment resulting from specialization. Although Simon (1988) found higher unemployment in more specialized cities, no research to date has examined whether they receive higher wages. This article studies the effects of regional industrial specialization on wages and unemployment using evidence from the U.S. labor market.

Section II reviews the sources of the benefits of industrial specialization. Section III informally models the effects of regional industrial specialization on unemployment and wages using a simple neoclassical model of the labor market. The relationship between employment risk and industrial specialization is discussed in Section IV. Section V introduces the empirical framework. The empirical results are presented in Section VI. Section VII addresses some issues yet to be resolved. We also address how our results fit into a world in which firms and workers enter into implicit contracts. Section VIII concludes with a brief summary.

II. The Benefits of Regional Concentration

One reason that firms within an industry locate near one another, noted by Ricardo, is to reduce the cost of transporting inputs, which are often regionally concentrated. Such firms, of course, may be forced to trade lower input-transportation costs for higher output-transportation costs. For example, steel firms that arose in Pennsylvania's Erie valley were able to outcompete other firms because of their proximity to coal and water transport facilities, and automobile firms that located near steel firms reduced the cost of transporting steel to the plant and automobiles to market. It is not surprising, therefore, that regions endowed with veins of ore specialize in mining activities, and regions located near water specialize in maritime activities.

[1] For evidence that regional unemployment is positively correlated with industrial specialization, see Simon (1988). For evidence that regional economic stability is inversely correlated with specialization, see Conroy (1975*a*), Kort (1981), and Brewer (1985). In addition, an independent literature in development economics has studied the link between nations' export specialization and the stability of export earnings; see James Love (1979) for recent empirical evidence.

External economies of scale provide an additional incentive for the geographic concentration of industry, as explained by George Stigler (1951). The production process of final output at a firm can be divided into stages, some of which are characterized by increasing costs, others by decreasing costs. Firms within an industry can reduce costs by increasing the scale of production of the stages characterized by decreasing costs. This can be accomplished if all firms (but one) abandon the stages of production characterized by decreasing costs and purchase the intermediate output from a single supplier.[2] The resulting scale economies are internal to the industry, but external to any one firm. Firms must often concentrate geographically to take advantage of these external scale economies. "The auxiliary and complementary industries that must operate in intimate cooperation can seldom do so efficiently at a distance" (Stigler 1951, p. 138).

III. The Cost of Regional Specialization

Although the benefits of regional industrial specialization are well known, the risk of specialization in the form of higher unemployment is often overlooked. Labor faces high mobility costs between geographic markets, which increases the cost of mobility between industries and, therefore, increases the probability of unemployment in the short run. The possibility that specialization causes employment instability was first recognized by McLaughlin (1930), who (wrongly) conjectured that industrially more diversified cities might be cyclically less sensitive. Later, Tress (1938) suggested that unemployment might be higher in more specialized cities. Since then, several studies have found a positive relationship between both employment instability and specialization (Conroy 1975*a*, 1975*b*; Kort 1981; Brewer and Moomaw 1985) and unemployment and specialization (Simon 1988).

We develop an informal model that relates an area's unemployment rate to its degree of industrial specialization. Firms in our model are distributed across industries and cities. Cities have different industry mixes and, in particular, different degrees of industrial specialization. In all that follows, goods are assumed to be sold in the national market with zero transport cost. Labor is assumed to be immobile between cities in the short run but perfectly mobile between industries within a city. Both labor and capital are assumed to be perfectly mobile between cities in the long run.

[2] The shedding of increasing-returns production stages requires a sufficiently high demand for the final product to support a large scale of production of the intermediate output. The larger an industry, therefore, the more likely that industry-specific transportation, parts suppliers, and specialized labor will develop to serve it. Examples include the textile industry in the South, the steel and auto industries in the Great Lakes region, Silicon Valley, and the concentration of high-technology firms in New England.

A. The Portfolio Effect of Specialization

Imagine a multi-industry world in which real shocks affect the demand for firms' output. The real shocks are assumed to be equivalent to observations on a random variable with zero mean, independently and identically distributed across industries. For simplicity, we assume that shocks to all firms within an industry are perfectly correlated, allowing us to carry out the analysis at the industry level.[3]

Consider a city with only one industry. When a worker is laid off, there is no alternative to unemployment in the short run. Now introduce many industries into the city. When layoffs occur in one industry it is almost certainly the case (by definition of real shocks—the overall level of labor demand is constant) that some other industries are expanding. A laid-off worker is, therefore, likelier to find employment in other industries in the diversified city. The diversity of potential employment opportunities creates a "portfolio effect" (see Barth et al. 1975; and Conroy 1975*b*) in the city labor market. Industrially more diversified cities will, on average, have lower rates of unemployment, while more specialized cities will have higher rates of unemployment.

B. Spatial Equilibrium

1. *Spatial Equilibrium in the Labor Market*

Assume that workers' utility is a function of the wage rate (W) and the probability of unemployment (U). Workers prefer higher wage rates and lower rates of unemployment. Firms can convince workers to accept a higher risk of unemployment by paying higher wages. If workers are homogeneous, all workers within a city face the same ex ante probability of unemployment and earn the same wage. Adding city subscripts, we write wages and the probability of unemployment within a city c ($c = 1, \ldots, C$) as W_c and U_c.

Because labor is perfectly mobile across cities in the long run, wage rates between cities will adjust to reflect the long-run probability of unemployment. If workers are risk neutral, long-run equilibrium requires that $W_c(1 - U_c) = W^* =$ a constant across cities. If workers are risk averse, the constraint is that $W_c(1 - U_c) + R(U_c) = V^* =$ another constant across cities, where R is a risk premium. This constraint can be rewritten implicitly as $W_c = W_c(V^*,U_c)$.

Because the probability of unemployment in a city is directly related to that city's degree of industrial specialization, $U_c = U_c(\text{SPECIALIZATION}_c)$, and $U'_c > 0$. Replacing this into the constraint for W_c, we obtain $W_c = W_c(V^*,\text{SPECIALIZATION}_c)$. Under the conditions above, the partial derivative of W_c with respect to SPECIALIZATION_c is positive.

[3] This assumption is overly strong. All that is required is that employment fluctuations within an industry be more highly correlated than between industries.

That is, workers who live in industrially more specialized labor markets must be compensated in the form of higher wage rates.

2. *Spatial Equilibrium among Firms*

Because capital is perfectly mobile across cities in the long run, its rate of return will be equalized across cities. Firms in more specialized cities must pay higher wages to compensate workers for the higher risk of unemployment. Firms will locate in specialized cities only if there are cost-reducing factors that offset the higher wages that must be paid to labor. We argued in Section II that firms located in more specialized cities to take advantage of the proximity to natural resources and external economies of scale. The existence of a wage premium paid to workers in more specialized cities, therefore, indirectly indicates the existence of these benefits.

IV. Labor-Market Risk and Industrial Specialization

In this section we present a measure of labor-market risk and show how it is related to industrial specialization. We borrow our concept of risk from portfolio theory and define a city-specific index of risk faced by the average worker. Michael Conroy (1975*a*, 1975*b*) first analyzed regional economic instability within a portfolio framework. In financial portfolio theory, the rate of return of each asset is subject to random fluctuations. Individuals buy portfolios of assets so as to maximize their expected rate of return (adjusted for risk aversion) subject to a given variance of that return. One widely used measure of portfolio risk is the variance of the rate of return of the portfolio. In the setting here, each city has a portfolio of industries, and each industry experiences fluctuations in the rate of employment growth. Our measure of risk is the variance of employment growth in each city implied by its industry mix.

A. The Relationship between Specialization and Employment Risk

In all that follows, industries are assumed to be national in scope. That is, the rate of employment growth in any one industry is assumed to be equal across cities. The change in employment in city c at time t is, then,

$$dE_{ct} = \sum_{i=1}^{I} dE_{ict} = \sum_{i=1}^{I} E_{ict} de_{it},$$

where E_{ict} is employment in industry i in city c at time t, dE_{ct} is the change in employment in city c, de_{it} is the rate of employment growth in industry i at time t, and I is the number of industries. Dividing through by total employment in the city at time t, E_{ct}, we obtain the rate of employment growth in the city:

$$dE_{ct}/E_{ct} = \sum_{i} E_{ict}/E_{ct} de_{it} = \sum_{i} S_{ict} de_{it},$$

where $S_{ict} = E_{ict}/E_{ct}$ is the employment share of industry i in city c at time t ($\sum_i S_{ict} = 1$), and the summation extends over all I industries. The S_{ict} defines the city's portfolio of employment at a moment in time. In the empirical work below, we construct the portfolio shares using only a single year of data. The time subscripts on the shares will therefore be dropped.

Our measure of risk, the variance of the rate of employment growth across industries in the city, is given by

$$\begin{aligned} \text{VAR}_c &= \sigma^2[\sum_i S_{ic} de_{it}] \\ &= \sum_i S_{ic}^2 \sigma_i^2 + \sum_i \sum_j S_{ic} S_{jc} \sigma_{ij} \quad (i \text{ not equal to } j), \end{aligned} \tag{1}$$

where $\sigma_i^2 = \sigma^2(de_{it})$ is the variance of the rate of employment growth of industry i over time, and $\sigma_{ij} = \sigma(de_{it}, de_{jt})$ is the covariance of the rate of employment growth in industries i and j over time. Other things equal, VAR_c is higher, the higher the variance of employment changes in any one industry and the more highly correlated are employment changes across industries.

A particularly important case of equation (1) results when industry employment growth rates are independently and identically distributed across industries. Then

$$\begin{aligned} \text{VAR}_c &= \sigma^2[\sum_i S_{ic}^2] \\ &= \sigma^2 \text{HERF}_c, \end{aligned} \tag{2}$$

where $\sigma_i^2 = \sigma^2$ for all i, $i = 1 \ldots, I$, and $\text{HERF}_c = \sum_i S_{ic}^2$ is the Herfindahl index of specialization in city c. According to this index, a city is defined to be perfectly specialized when its employment is concentrated in a single industry and perfectly diversified when employment is evenly distributed across all industries. If the city is completely specialized, that is, all employment in the city is concentrated in a single industry, then $S_{ic} = 1$ for that industry and zero for all others, and the index of specialization is equal to one. If the city is perfectly diversified, that is, all employment in the city is evenly distributed across all I industries, then $S_{ic} = 1/I$ for all industries and HERF_c takes on its minimum of $1/I$. The degree of specialization is, therefore, positively related to the Herfindahl index of employment. In sum, both the probability of unemployment and earnings will be positively related to HERF_c.[4]

[4] The variable HERF_c only measures the degree of specialization within a city. It is not intended to proxy for the existence of external economies of scale or locational economies. Consider an industry of given absolute size in two cities with different populations. External economies are related to the absolute size of

B. The Geographic Pattern of Industrial Specialization and Risk

We constructed the Herfindahl index of specialization for each of 43 standard metropolitan statistical areas (SMSAs). We divided employment into 28 industries: 20 2-digit Standard Industrial Classification (SIC) manufacturing industries, plus 8 others: agriculture; mining; construction; transport and public utilities; wholesale trade; retail trade; finance, insurance, and real estate; and services. *County Business Patterns, 1977* (U.S. Bureau of the Census 1979) was the primary data source for employment; the economic censuses were used as secondary sources.[5] The city-level data and sources are listed in table A1 in Appendix A.

The pattern of specialization as measured by the 28-industry Herfindahl, HERF (the city subscripts are now dropped), is shown in column 1 of table 1. The mean value of the specialization index was .135, with a standard deviation of .024. The range of specialization was considerable; the cities in our sample spanned about 5.4 standard deviations. No obvious patterns emerged. Despite the omission of the government sector in the analysis, Washington, D.C., was the most specialized city in the sample, with most employment in the service and financial sectors. It was followed by Sacramento, Norfolk, Gary, and Tampa. The average value of the specialization index in the five most specialized cities was .182, or about 2 standard deviations above the mean. The five least specialized cities were Greensboro, Paterson, Newark, Los Angeles, and Buffalo. The average value of specialization for these cities was .104, or 1.3 standard deviations below the mean. New York, often considered to be among the most diverse of cities, was the tenth most specialized, while Detroit, often considered to be among the most specialized of cities, was twenty-fourth.

This somewhat unexpected pattern of specialization resulted partially from aggregating manufacturing and nonmanufacturing industries. The regional and international literature distinguish between industries that produce goods to be exported to the national market and industries that supply goods to the local market. A more recognizable pattern of specialization resulted when the index of specialization was calculated for the export sector alone, assumed to include the 20 manufacturing industries,

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an industry and not its size relative to the size of other industries within a city. Industry-specific external economies of scale will be identical, but measured specialization will probably differ in the two cities.

[5] The economic censuses include U.S. Bureau of the Census (1977*a*, 1977*b*, 1977*c*). To preserve confidentiality, *County Business Patterns* occasionally provided only an interval estimate for an industry's employment. In these cases, if a noninterval estimate was available from the economic censuses (construction, manufacturing, retail trade, wholesale trade, or services), this number was used; otherwise, the midpoint of the *County Business Pattern* interval was used. Although *CBP* provided an estimate of total SMSA employment, total employment here is calculated by summing employment in each individual industry to ensure that the shares sum to one.

Table 1
Industrial Specialization

				Manufacturing Sector		
					Largest Industry	
City	HERF (1)	$HERF_N$ (2)	$HERF_M$ (3)	Share of E_c (4)	Industry (5)	Share of E_{Mc} (6)
1. New York	.1466	.2270	.1288	.22	Apparel	.28
2. Los Angeles	.1201	.2367	.0888	.31	Transport	.19
3. Chicago	.1180	.2272	.0899	.31	Electric machinery	.15
4. Philadelphia	.1302	.2447	.0689	.29	Machinery	.10
5. Detroit	.1234	.2454	.1790	.36	Transport	.34
6. San Francisco	.1442	.2017	.0743	.16	Food	.13
7. Washington	.2266	.2591	.2088	.07	Printing	.39
8. Boston	.1503	.2593	.0896	.25	Electric machinery	.18
9. Nassau-Suffolk	.1466	.2474	.1172	.25	Transport	.23
10. Pittsburgh	.1290	.2319	.1901	.31	Primary metals	.39
11. St. Louis	.1230	.2320	.1028	.30	Transport	.23
12. Baltimore	.1328	.2329	.0879	.26	Electric machinery	.15
13. Cleveland	.1121	.2327	.1094	.35	Machinery	.18
14. Houston	.1240	.1997	.1068	.23	Machinery	.19
15. Newark	.1053	.2117	.0880	.33	Chemicals	.17
16. Minneapolis	.1364	.2274	.1160	.25	Machinery	.25
17. Dallas/Fort Worth	.1152	.2056	.0893	.27	Electric machinery	.16
18. Seattle	.1334	.2141	.2175	.25	Transport	.44
19. Anaheim	.1288	.2466	.1078	.31	Electric machinery	.22
20. Milwaukee	.1147	.2388	.1402	.37	Machinery	.27
21. Atlanta	.1339	.1933	.0892	.18	Transport	.20
22. Cincinnati	.1189	.2349	.0927	.32	Transport	.15
23. Paterson	.0966	.2308	.0891	.40	Electric machinery	.14
24. San Diego	.1586	.2487	.1356	.22	Transport	.27
25. Buffalo	.1159	.2486	.0982	.36	Machinery	.16
26. Miami	.1572	.2253	.1012	.17	Apparel	.25
27. Kansas City	.1274	.2141	.0843	.24	Transport	.13
28. Denver	.1366	.2128	.0758	.21	Food	.14
29. San Bernadino	.1550	.2552	.0790	.23	Primary metals	.15
30. Indianapolis	.1145	.2083	.1252	.30	Transport	.24
31. San Jose	.1291	.2699	.1810	.38	Electric machinery	.32
32. New Orleans	.1492	.2088	.1285	.16	Transport	.24
33. Tampa	.1670	.2396	.0894	.17	Food	.17
34. Portland	.1295	.2187	.0757	.24	Instruments	.13
35. Columbus	.1332	.2365	.0918	.27	Fabricated metals	.14
36. Rochester	.1371	.2682	.2698	.43	Instruments	.49
37. Sacramento	.1860	.2432	.1259	.13	Food	.27
38. Birmingham	.1140	.1977	.1324	.28	Primary metals	.27
39. Albany	.1483	.2702	.1252	.28	Machinery	.29
40. Norfolk	.1608	.2226	.1374	.16	Transport	.26
41. Akron	.1195	.2215	.2047	.34	Rubber	.38
42. Gary	.1692	.2374	.4709	.46	Primary metals	.68
43. Greensboro	.0900	.2040	.1353	.44	Textiles	.27

mining, and agriculture (hereafter referred to as "manufacturing" for ease of exposition). Although this aggregation is misleading for the larger cities, which are likely to export goods and services outside the manufacturing sector, this classification has intuitive appeal.

Table 1 (col. 3) shows the degree of specialization within manufacturing,

HERF_M. Column 4 shows the proportion of each city's total employment, E_c, employed in the manufacturing sector. The largest industry within the manufacturing sector and its employment share as a fraction of total manufacturing employment (E_{Mc}) are shown in columns 5 and 6. Again, the range of specialization was wide. Gary had both the largest and most specialized manufacturing sector; 46% of employment was in manufacturing, and 68% of manufacturing employment was in primary metals (SIC 33). Detroit had the sixth most concentrated manufacturing sector, with 34% of manufacturing employment in transportation (SIC 37). At the other end of the spectrum, the manufacturing sector employed only 16% of San Francisco's work force, where the dominant manufacturing industry was foods (SIC 20) with 13% of manufacturing employment.

Finally, we computed the Herfindahl index for the nonmanufacturing sector, HERF_N, shown in column 2 of table 1. This index, however, seems less meaningful than the overall and manufacturing Herfindahls because of the high degree of aggregation—two-thirds of total employment was distributed across the six nonmanufacturing industries. Although it would be desirable to further disaggregate the data, the added burden was sufficiently large to leave this task for future research.

Summary statistics for the Herfindahls are in rows 1–3 of table 2.

C. A More General Index of Employment Risk

The Herfindahl index of specialization measures the employment risk faced by a typical worker in a city as defined in equation (1), VAR, only under relatively stringent conditions—when employment growth is independently and identically distributed across industries (see eq. [2]). As pointed out to us, however, this condition is unlikely to be satisfied in reality.[6] A city that is well diversified in a set of industries whose employment is highly positively correlated is more risky than an equally diversified city whose industries are uncorrelated.

We computed the variance of each city's portfolio of employment in equation (1) from detrended nationwide industry employment growth rates.[7] As in the case of the Herfindahl indexes of specialization, the variance was computed for all 28 industries together (VAR), within manufacturing (VAR_M), and within nonmanufacturing (VAR_N). Summary statistics for these indexes are shown in rows 4–6 of table 2.

Clearly, the correlation between the variances and Herfindahls need not be positive; cities may tend to specialize in stable industries. The correlations

[6] To see why this may be important, consider the pathological case in which $\sigma_i^2 = \sigma_{ij} = \sigma_2$, i.e., employment growth rates are identically distributed and perfectly correlated across industries. Then $\text{VAR}_c = (\sum_i S_{ic}^2 + \sum_i \sum_j S_{ic}S_{jc})\,\sigma^2 = \sigma^2\ (i \neq j)$, and no amount of diversification can reduce employment risk in the city.

[7] Specifically, the growth rate in industry i at time t was computed as the first difference of the natural logarithm of employment. We regressed these growth rates on time and retrieved the residual growth rate.

Table 2
Summary Statistics and Selected Simple Correlations between Measures of Specialization and Risk in 43 SMSAs

		Correlation		
	Mean	HERF	$HERF_M$	$HERF_N$
1. HERF	.1351 [.024]	1.0000	.2867 (.06)	.3809 (.01)
2. $HERF_M$	.1288 [.070]	...	1.000	.2227 (.15)
3. $HERF_N$	.2310 [.02]	...	...	1.0000
4. VAR	71.98 [22.23]	−.3733 (.01)	...	...
5. VAR_M	24.23 [65.66]	...	.5157 (.00)	...
6. VAR_N	34.71 [3.45]	...	...	−.5131 (.00)
7. CVAR	71.37 [22.02]	−.3790 (.01)	...	...
8. $CVAR_M$	24.02 [64.15]	...	.4971 (.00)	...
9. $CVAR_N$	33.83 [3.48]	...	...	−.5416 (.00)
10. UVAR	.062 [.035]	.4093 (.01)	...	...
11. $UVAR_M$	.207 [.24]	...	.8912 (.00)	...
12. $UVAR_N$	.088 [.01]	...	...	.9314 (.00)
13. $CYCLE_M$	.0106 [.0041]	...	...	...
14. $CYCLE_N$	.0355 [.0043]	...	...	...

NOTE.—43 observations. All variances were multiplied by 10,000. Probability values are in parentheses; standard deviations are in brackets.

in table 2 (rows 4–6) show that, indeed, HERF and VAR were negatively correlated. This negative correlation was due to the nonmanufacturing sector. The correlation between $HERF_N$ and VAR_N was a highly significant −.5131. On closer examination, we discovered that cities with high values of $HERF_N$ tended to have a large service sector (a very stable industry) and a small construction sector (a very volatile industry). By contrast, there was a highly significant positive correlation between $HERF_M$ and VAR_M of .5157.

Clearly, the Herfindahl indexes of specialization do not completely measure the overall level of employment risk in a city as defined by equation (1). It can, however, be shown that they measure one component of this risk, under certain conditions. Specifically, VAR can be divided into two independent parts, one that is proportional to HERF, and another that measures the remaining component of risk.

Suppose that employment growth in industry i at time t is given by

$$de_{it} = \beta_{it} + \varepsilon_{it}, \tag{3}$$

where

$$E(\beta_{it}\varepsilon_{jt}) = 0 \quad \text{for all } i \text{ and } j,$$

$$E(\beta_{it}\beta_{jt}) = \sigma_{ij} \quad \text{for all } i \text{ and } j,$$

$$E(\varepsilon_{it}\varepsilon_{jt}) = 0 \quad \text{for } i \text{ not equal to } j,$$

and

$$E(\varepsilon_{it}^2) = \sigma_{i\varepsilon}^2 \quad \text{for all } i.$$

Rewriting equation (1) and adding appropriate subscripts, we write a city's level of risk as

$$\begin{aligned} \text{VAR} &= \sum_i \sum_j S_i S_j \sigma_{ij} + \sum_i S_i^2 \sigma_{i\varepsilon}^2 \quad (i \text{ not equal to } j) \\ &= \text{CVAR} + \text{UVAR}. \end{aligned} \tag{4}$$

If, in addition, we assume that $\sigma_{i\varepsilon}^2 = \sigma_\varepsilon^2$ for all i, we have

$$\text{VAR} = \text{CVAR} + \sigma_\varepsilon^2 \text{HERF}. \tag{5}$$

The σ_{ij} (and σ_ε^2) in equation (4) can be estimated using factor analysis. In factor analysis, variables are divided into common factors and unique factors. A common factor is an unobservable, hypothetical variable that contributes to the variance of at least two variables. One obvious example of a common factor is the business cycle. Between-industry correlation of the de_{it} occurs only through the common factor, here β_{it}. A unique factor can contribute to the variance of only a single variable. The unique factors here, the ε_{it}, play the role of industry-specific shocks.

The term CVAR is a function of a city's industry mix above and beyond specialization. Because CVAR arises from the common factor, β_{it}, we refer to it as the common-factor component of VAR. The second term in equation (4) is referred to as the unique-factor component of VAR. If the ε_{it} are independently and identically distributed (i.i.d.), UVAR is proportional to a city's degree of specialization, and VAR is given by equation (5).

Because dynamic factor analysis is a complex procedure, and because our focus is on specialization rather than the exact empirical magnitude of the σ_{ij} and $\sigma_{i\varepsilon}$, we estimated equation (3) for the 28 industries in the sample using principal factor analysis (specifically, the FACTOR procedure in Statistical Analysis System [SAS], METHOD = PRINCIPAL, PRIORS = SMC).[8] Although equation (3) includes only a single common factor, β_{it}, in practice there are likely to be multiple common factors. In the absence of any a priori restrictions, the question of how many common factors to extract arose. As already noted, if the ε_{it} were truly i.i.d., the unique factor variance would be proportional to HERF. A useful guideline, therefore, was to continue to extract common factors so as to maximize the correlation between the unique-factor variances and the Herfindahl indexes of specialization. The maximum correlation between UVAR_M and HERF_M, and UVAR_N and HERF_N, occurred at nine factors (see rows 11–12 of table 2).[9]

The common-factor and unique-factor components of VAR, VAR_M, and VAR_N are listed for the 43 SMSAs in table 3. The pattern of the variances is not unexpected; cities with high common-factor variances are highly sensitive to the business cycle and include Detroit, San Jose, Gary, Rochester, and Pittsburgh. Somewhat striking were the relative sizes of the common-factor and unique-factor variances: the common-factor variances dwarfed the unique-factor variances in magnitude. The relative magnitudes might suggest that any differences across cities in unemployment and earnings due to industrial diversity would be minor compared to those generated by the common-factor variance. The evidence below, however, indicates just the opposite—the effects of the unique-factor variance (and, by implication, industrial specialization) are larger by a factor of 100 than the effects of the common-factor variances. We suggest a possible reason for this finding in Section VII.

The correlations between specialization and the factor variances are shown in table 2 (rows 7–12).

V. Empirical Framework

In this article, we study the link between wages, unemployment, and industrial specialization in 43 large U.S. cities (SMSAs).[10] Our empirical

[8] Although regular factor analysis is applicable with panel data only under certain conditions, it seems unlikely that using dynamic factor analysis would change substantially the empirical results in Sec. VI. For a recent example of the use of dynamic factor analysis, see Norrbin and Schlagenhauf (1988).

[9] We attempted to use the maximum-likelihood procedure in SAS. However, the unrestricted procedure resulted in two Ultra-Heywood cases, which invalidate the solution. In an Ultra-Heywood case, the unique variance is negative. Maximum likelihood is only the preferred method because of its large-sample statistical properties, which are unlikely to hold in the present sample, given that there are only 34 observations over time on each of the 28 industries. We therefore settled on the simplest and most commonly used method of factor analysis.

[10] Cities are a more relevant unit of analysis than states to the extent that agglomeration economies decrease with distance. A parts supplier in the same city offers greater cost advantages than a parts supplier in the same state.

Table 3
Estimated Common-Factor and Unique-Factor Variances of City Employment

City	Common-Factor CVAR	$CVAR_M$	$CVAR_N$	Unique-Factor UVAR	$UVAR_M$	$UVAR_N$
1. New York	4.073	13.541	2.700	.052	.066	.080
2. Los Angeles	7.372	25.548	3.086	.056	.146	.090
3. Chicago	7.143	24.435	3.097	.038	.090	.085
4. Philadelphia	6.092	19.825	3.059	.045	.054	.094
5. Detroit	10.221	35.544	3.135	.102	.476	.094
6. San Francisco	4.842	17.773	3.475	.047	.060	.068
7. Washington	3.646	11.500	3.337	.085	.120	.100
8. Boston	5.911	23.697	2.887	.057	.090	.101
9. Nassau-Suffolk	6.534	28.516	3.056	.067	.190	.096
10. Pittsburgh	9.010	31.769	3.608	.054	.496	.091
11. St. Louis	7.351	25.503	3.305	.061	.227	.087
12. Baltimore	6.557	23.068	3.376	.045	.123	.088
13. Cleveland	9.368	31.603	3.210	.045	.123	.089
14. Houston	6.385	18.619	4.296	.054	.104	.088
15. Newark	6.958	21.118	3.164	.035	.055	.075
16. Minneapolis	6.299	24.734	3.175	.049	.120	.086
17. Dallas/Fort Worth	7.051	24.426	3.587	.048	.110	.076
18. Seattle	7.135	30.323	3.417	.092	.631	.079
19. Anaheim	8.252	30.268	3.375	.053	.133	.095
20. Milwaukee	9.456	30.568	3.135	.049	.162	.091
21. Atlanta	5.167	18.838	3.584	.050	.140	.068
22. Cincinnati	7.047	22.465	3.198	.050	.015	.090
23. Paterson	7.984	20.994	3.036	.036	.086	.088
24. San Diego	6.396	29.070	3.435	.077	.249	.096
25. Buffalo	8.992	28.547	3.256	.048	.174	.095
26. Miami	4.442	15.656	3.181	.057	.055	.081
27. Kansas City	6.069	21.045	3.443	.047	.106	.080
28. Denver	5.633	17.591	3.836	.053	.054	.085
29. San Bernadino	6.434	23.793	3.565	.055	.166	.098
30. Indianapolis	7.990	29.719	3.429	.054	.206	.072
31. San Jose	10.983	36.505	3.215	.076	.248	.108
32. New Orleans	4.989	16.077	3.798	.060	.269	.076
33. Tampa	4.824	17.166	3.401	.062	.065	.092
34. Portland	6.286	22.900	3.368	.044	.056	.082
35. Columbia	6.535	23.753	3.167	.046	.086	.088
36. Rochester	9.485	26.436	2.930	.078	.244	.106
37. Sacramento	4.301	12.868	3.510	.072	.098	.093
38. Birmingham	7.598	24.067	4.034	.042	.349	.080
39. Albany	6.417	22.467	2.992	.061	.168	.107
40. Norfolk	5.382	20.552	3.867	.072	.258	.086
41. Akron	9.674	30.780	3.668	.063	.454	.083
42. Gary	15.772	39.919	4.212	.268	1.485	.096
43. Greensboro	8.828	19.378	3.875	.043	.155	.079

NOTE.—All variances were multiplied by 10,000.

analysis of wage and unemployment determination within cities is based on a sample of 38,128 privately employed labor-force participants selected from the demographic files of the (March) 1977, 1978, and 1979 Current Population Surveys (CPS). Many observations, unfortunately, had to be deleted because the CPS survey (in those years) identified the SMSA of residence only for households in the 43 largest SMSAs.[11] Individuals were included in the empirical analysis if they were between the ages of 20 and 65, were labor force participants full time for at least 26 weeks in the previous year, were privately employed outside of the household sector, and worked for pay. These selection criteria eliminated individuals who had no earnings for the previous year. Finally, we deleted individuals from the sample if their earnings were imputed by the census.

Before turning to the specification of the empirical model, we briefly discuss city-level variables other than specialization that affect unemployment and earnings.

A. Industry Mix and the Business Cycle

The industry mix of labor markets can be expected to affect both unemployment and earnings. For example, durable goods industries are more sensitive to the business cycle than nondurables. We constructed indexes to control for differences across cities in industry mix within the manufacturing and nonmanufacturing sectors, denoted $CYCLE_M$ and $CYCLE_N$, respectively. These indexes are essentially city employment-share-weighted sums of national industry growth rates. Their construction is outlined in Appendix B. Assuming that fluctuations in labor demand are the dominant source of employment flows, the probability of unemployment should be negatively related to both $CYCLE_M$ and $CYCLE_N$. We also included $CYCLE_M$ and $CYCLE_N$ in the wage regressions. We expected wages to rise in cities with growing industries and fall in cities with declining industries.[12] In theory, however, $CYCLE_M$ and $CYCLE_N$ reflect the forces of both supply and demand, so that signing their coefficients is not straightforward.

B. Firm Size

It is well known that earnings are positively related to firm size. In addition, research by Evans and Leighton (1989) suggested that workers in larger firms have greater employment stability than workers in smaller firms. The source of this stability is not clear but may have something to do with the same (unobserved) worker characteristics that underlie the positive earnings-firm-size relationship.[13] We computed each industry's average firm size by city (the number of employees divided by the number of firms), FIRM SIZE, and matched individuals in the CPS by industry and city based on their reported industry during the previous year.[14] We

[11] The CPS actually identifies 44 separate urban areas; however, Dallas and Fort Worth, separately identified in the CPS, combine to form a single SMSA.

[12] Topel (1986) provides empirical evidence regarding the dynamics of demand, wages, and unemployment.

[13] For a review of the literature and a model explaining this relationship, see Garen (1985).

[14] Individuals report the industry of what they considered their main job during the previous year. There is therefore a possibility of data errors for individuals who

entered FIRM SIZE as an explanatory variable in both the wage and unemployment regressions. Given the findings of Evans and Leighton, we expected lower unemployment rates among workers employed in larger firms.

C. City Size

It has long been hypothesized that quality of life is related to city size. For example, congestion and crime rates are higher in larger cities. Individuals must, therefore, be compensated with higher wage rates to endure the disutility of living in larger cities.[15] The question arises of how firms in larger cities can afford to pay the higher wages necessary to attract workers. Just as there are industry-specific external scale economies, there are local scale economies enjoyed by firms in all industries, or aggregate scale economies (Carlino 1982). Examples of decreasing-cost industries that are more efficient at the greater scale possible in larger cities include newspapers, restaurants, bookstores, public transportation, city operas, and power plants. CITY SIZE, defined as 1976 population (in millions), was entered as a regressor in the earnings equations.

VI. Results

A. Unemployment Equations

Our dependent variable is the fraction of weeks in the labor force that an individual spent unemployed in the previous calendar year.[16] It is defined as the number of weeks spent looking for work divided by the number of weeks in the labor force (the number of weeks in the labor force equals the sum of weeks unemployed and weeks employed).[17]

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switched jobs. In addition, FIRM SIZE could not be calculated for all workers in the CPS sample. This arose when an individual in the CPS reported being employed in a particular industry for which *County Business Patterns* reports zero employment in that city. This could result from sampling or reporting error in *CBP* or reporting error in the CPS. In these cases, we assigned the samplewide average FIRM SIZE for the reported industry rather than delete the observation.

[15] See Clark, Kahn, and Ofek (1987) for a literature review, analysis, and empirical evidence of the effects of city size on earnings and the quality of life.

[16] Other authors who have used a similar approach to the study of unemployment include Abowd and Ashenfelter (1981) and Murphy and Topel (1987). Abowd and Ashenfelter examined the number of hours an individual spent unemployed in a year. Murphy and Topel used the retrospective information from the CPS to estimate a hazard model of unemployment.

[17] Logit unemployment regressions estimated using data on current employment status yielded mixed results, depending on the month of the CPS used. We found a positive and significant effect of specialization using the May surveys (Simon 1987) but an insignificant effect using the March surveys. There was a positive and significant effect using aggregate data, where the dependent variable was the annual average unemployment rate in a city (Simon 1988). The relevant question is the long-run effect of specialization on unemployment, hence our choice of dependent variable.

Table 4
Means and Standard Deviations of City and Individual Characteristics

	Mean	SD
City traits:*		
City size (millions)	2.149	1.848
Firm size (thousands)	16.473	2.454
Individual traits:†		
Unemployment rate	.050	.150
Probability of unemployment spell	.161	.368
Weekly wage	284.435	174.438
Hours worked per week	42.031	6.791
Education	12.378	2.938
Experience	19.033	13.173
Experience^2	535.773	609.258
Married	.662	.473
Female	.362	.481
Married female	.190	.392
Nonwhite	.128	.335
1977	.330	...
1978	.332	...
1979	.338	...

* 43 observations.
† 38,128 observations.

The following model of unemployment was specified:

$$U_i = f(X_i; \text{SPECIALIZATION, CVAR, } \text{CYCLE}_M, \text{CYCLE}_N; \text{FIRM SIZE}), \tag{6}$$

where U_i = the fraction of weeks in the labor force looking for work last year, and X_i = a vector of traits of individual i. The vector X_i included education, labor market experience (age minus schooling minus six), marital status, sex, and race. In addition, some specifications included a complete set of 27 separate industry intercepts. Individuals were matched by city to the variables SPECIALIZATION, CYCLE$_M$, and CYCLE$_N$ and by industry and city to FIRM SIZE.[18] Table 4 lists the variables in the analysis along with their summary statistics.

We estimated several versions of equation (6) using Tobit.[19] The effects of the control variables on unemployment were consistent with models of

[18] Because unemployed individuals are especially likely to switch industries, the meaning of the industry dummy variables and FIRM SIZE is not clear-cut. These variables do, however, help control for industry-specific differences in layoff rates. Omitting the industry dummies leaves our main econometric findings intact.

[19] It was necessary to use Tobit because the dependent variable is censored (at zero) and because of the large number of observations (84%) that had values of zero for the dependent variable. For example, Abowd and Ashenfelter (1981) used Heckman's selectivity correction in their analysis, where the dependent variable was defined as the number of hours an individual spent unemployed in the previous year.

unemployment estimated by other researchers. More educated, older, and married individuals were less likely to be unemployed; married females and nonwhites were more likely to be unemployed. The cyclical demand indicators generally entered negatively, not a surprising result.

We consider first the estimates of (6) in which SPECIALIZATION was measured using HERF (the 28-industry Herfindahl). Columns 1–3 of table 5 report the results for the sample as a whole, and separately for subsamples of manufacturing and nonmanufacturing workers. The estimated coefficient on HERF was always significantly positive. We next replaced HERF with sector-specific Herfindahls, $HERF_M$ and $HERF_N$, for the subsamples of manufacturing and nonmanufacturing workers (cols. 4 and 5 of table 5). The estimated coefficients on specialization were both positive, but the estimated coefficient on $HERF_N$ was statistically insignificant (t = 1.3).

Table 5
Tobit Unemployment Regressions, by CPS Subsample and Herfindahl

	All HERF (1)	Manufacturing HERF (2)	Nonmanufacturing HERF (3)	Manufacturing $HERF_M$ (4)	Nonmanufacturing $HERF_N$ (5)
City traits:					
Specialization	1.221	2.114	.706	.597	.512
	(4.0)	(3.6)	(1.9)	(3.3)	(1.3)
Common-factor variance	−49.993	80.939	−113.55	5.979	−741.73
	(.9)	(.9)	(1.6)	(.2)	(3.3)
$CYCLE_M$	−11.129	−11.415	−9.449	−11.639	−9.374
	(4.0)	(2.6)	(2.6)	(2.4)	(2.9)
$CYCLE_N$	−16.937	−11.640	−15.711	−4.842	−6.253
	(6.4)	(2.4)	(4.8)	(1.3)	(1.9)
Firm size	−.184*	−.210*	−8.888*	−.224*	−8.119*
	(3.8)	(4.0)	(5.5)	(4.3)	(4.9)
Individual traits:					
Education	−.033	−.029	−.036	−.029	−.036
	(19.4)	(10.9)	(16.1)	(10.9)	(16.2)
Experience	−.009	−.009	−.009	−.009	−.009
	(22.6)	(14.0)	(17.9)	(14.0)	(18.1)
Married (yes = 1)	−.218	−.208	−.221	−.210	−.220
	(17.7)	(10.3)	(14.2)	(10.4)	(14.2)
Female (yes = 1)	−.107	−.043	−.133	−.044	−.133
	(7.4)	(1.7)	(7.7)	(1.7)	(7.7)
Married female (yes = 1)	.196	.188	.193	.190	.195
	(10.4)	(5.8)	(8.4)	(5.8)	(8.4)
Nonwhite (yes = 1)	.108	.106	.113	.103	.111
	(8.6)	(5.0)	(7.2)	(4.9)	(7.1)
Intercept	.702	.482	.916	.525	.746
	(7.2)	(2.7)	(7.7)	(3.2)	(5.4)
−Log likelihood	14,831	5,069.7	9,727.4	5,071.0	9.716.5
Observations	38,128	13,289	24,839	13,289	24,839

NOTE.—Absolute value of asymptotic t-statistics in parentheses. All regressions include dummy variables for year and industry.
* Coefficient multiplied by 1,000.

Broadly similar results were obtained when the industry dummy variables were omitted (panel A of table 6). The main difference is that the coefficient on $HERF_N$ entered significantly.

Next, each of the Herfindahl indexes of specialization was replaced by its corresponding unique-factor variance (see table 6, panels B [industry dummies included] and C [industry dummies not included]). Except for $UVAR_N$ (col. 5), unemployment was significantly positively related to the unique-factor variances, as hypothesized.

The effects of the common-factor variances on unemployment were generally weak. We can think of at least two reasons. First, the indexes of

Table 6
Tobit Unemployment Regressions, Further Results by CPS Subsample

A. With Herfindahls, No Industry Dummies Included

	All HERF (1)	Manufacturing HERF (2)	Nonmanufacturing HERF (3)	Manufacturing $HERF_M$ (4)	Nonmanufacturing $HERF_N$ (5)
Specialization	1.314	2.117	.679	.582	.809
	(4.3)	(3.8)	(1.8)	(3.4)	(2.0)
Common-factor variance	32.855	126.241	−36.418	29.388	−353.91
	(.6)	(1.4)	(.5)	(1.3)	(1.6)

B. With Estimated Unique-Factor Variance, Industry Dummies Included

	All UVAR (1)	Manufacturing UVAR (2)	Nonmanufacturing UVAR (3)	Manufacturing $UVAR_M$ (4)	Nonmanufacturing $UVAR_N$ (5)
Unique-factor variance	10897.1	12227.7	8107.8	1462.4	4905.1
	(4.3)	(2.7)	(2.3)	(2.1)	(.7)
Common-factor variance	−194.74	−66.128	−226.4	−11.707	−872.04
	(2.9)	(.6)	(2.5)	(.4)	(4.6)

C. With Estimated Unique-Factor Variances, Industry Dummies Not Included

	All UVAR (1)	Manufacturing UVAR (2)	Nonmanufacturing UVAR (3)	Manufacturing $UVAR_M$ (4)	Nonmanufacturing $UVAR_N$ (5)
Unique-factor variance	12044.9	13669.6	7487.8	1506.1	10761.1
	(4.4)	(3.1)	(2.1)	(2.3)	(1.5)
Common-factor variance	−130.29	−47.809	−139.81	8.773	−539.93
	(1.8)	(.4)	(1.5)	(.3)	(2.8)

NOTE.—Absolute value of asymptotic t-statistics in parentheses. Regressions include the same individual traits and other control variables as the regressions in table 5.

cyclical fluctuations, CYCLE_M and CYCLE_N, control for the contemporaneous effects of the business cycle, which is an important common factor. Second, the common-factor variances are probably dominated by business-cycle effects. Unemployment at a moment in time can be either higher or lower in cities that are cyclically more sensitive; that is, lower during business cycle peaks and higher during troughs. Generally, the higher unemployment during the trough outweighs the lower unemployment during the peak so that unemployment rates averaged over the business cycle are higher in cyclically more sensitive cities. The average business cycle, however, lasts on the order of 3 years, while the CPS provides information about unemployment only over the preceding year. This may, therefore, account for our failure to pick up the positive effect of cyclical sensitivity on long-run unemployment. Indeed, national unemployment fell over the 1977–79 period from 7.1% to 5.8%.

We illustrate the effect of industrial specialization on unemployment using the estimated coefficient on specialization in column 1 of table 5. Noting that about 16% of the sample experienced an unemployment spell, each standard deviation increase in overall specialization (.024 units) was estimated to increase the fraction of weeks in a year that an individual would have been unemployed by about ($1.221 \times .16 \times .024$) .47 percentage points. The mean fraction of weeks spent unemployed was 5.65%, so this translates into an increase of about 8.3%. To take an admittedly extreme case, our estimates indicate that the fraction of weeks spent unemployed for an individual who moved from Greensboro to Washington would have increased by ($[.2266-.0900] \times 1.221 \times .16$) 2.7 percentage points, other things equal.[20] The five most specialized cities, with an average value of specialization of .182 (.047 units above the mean), had a rate of unemployment about ($1.221 \times .16 \times .047$) 0.9 percentage points higher due to above-average specialization. By contrast, the five least specialized cities, with an average value of specialization of .104 (.031 units below the mean) had a 0.6 percentage point lower probability of unemployment due to below-average specialization.

B. Earnings Equations

The results of the previous section indicated that individuals who lived in industrially more specialized cities were subject to a higher probability of unemployment. The theory of compensating differences predicts that this higher probability of unemployment will be compensated in the form of higher wage rates. We estimated the following log-linear earnings function:

[20] The estimated effect of specialization on unemployment is probably less accurate for extremely specialized or diversified cities. This contrast is, therefore, most likely overstated.

$$\log(\text{WEEKLY WAGE}_i) = g(X_i;\ \text{SPECIALIZATION, CYCLE}_M,\ \text{CYCLE}_N,\ \text{CVAR, CITY SIZE};\ \text{FIRM SIZE}). \quad (7)$$

The main difference between the explanatory variables in equation (7) and equation (6) is the addition of CITY SIZE. Weekly earnings were calculated for each individual as wage and salary income received divided by the number of weeks worked during the previous year.

Equation (7) was estimated using ordinary least squares. In addition to the 27 separate industry intercepts, the vector X_i included hours worked per week, education, experience, experience squared, sex, race, and marital status. Industry dummy variables were included to pick up the otherwise unexplained wage variation across industries.[21] The coefficients on the industry dummy variables are not reported to save space. The estimated coefficients on individual traits were similar to those estimated by other authors. Wages were significantly positively related to CITY SIZE, as anticipated. Also, not surprisingly, wages were higher in cities with higher values of CYCLE_M and CYCLE_N.

Again, we first focus on the results using the 28-industry specialization index, HERF (cols. 1–3 of table 7). The estimated coefficients were positive and significant, except in the manufacturing subsample ($t = 1.2$). We again divided the sample into manufacturing and nonmanufacturing workers, replacing HERF by the sector-specific indexes HERF_M and HERF_N. The coefficient on HERF_M was positive and significant, while the coefficient on HERF_N was positive but insignificant ($t = 1.0$). Finally, we replaced the Herfindahls with the unique-factor variances (table 8). In every case, we found higher wage rates in cities with higher unique-factor variances, significant except for the coefficient on UVAR_N (col. 5). As in the case of the unemployment equations, the estimated coefficients on the unique-factor variances dwarfed those on the common-factor variances in size, although not in significance.

With one exception (CVAR_N), and in contrast to the unemployment equations, the estimated coefficients on the common-factor variances were positive and statistically significant. Above, we argued that cities with higher common-factor variances tended to be cyclically more sensitive and, therefore, would have higher long-run rates of unemployment (although not necessarily at a given point in time). Firms in cyclically more sensitive cities, then, would have to compensate workers for the higher long-run

[21] Authors disagree about the source of these differentials. Some argue that they reflect payment of efficiency wages (Krueger and Summers 1988), while others argue that they capture unobservable individual differences that are correlated with industry (Topel 1989).

Table 7
Log Weekly Wage Regressions by CPS Subsample and Herfindahl

	All HERF (1)	Manufacturing HERF (2)	Nonmanufacturing HERF (3)	Manufacturing $HERF_M$ (4)	Nonmanufacturing $HERF_N$ (5)
City traits:					
Specialization	.567	.326	.696	.255	.221
	(3.8)	(1.2)	(3.8)	(3.1)	(1.0)
Common-factor variance	132.37	179.57	115.19	29.251	−273.26
	(4.6)	(4.3)	(3.0)	(2.9)	(1.9)
Firm size	17.860	14.028	253.34	13.916	279.56
	(8.8)	(6.9)	(3.4)	(6.6)	(3.7)
City size	.016	.007	.020	.006	.016
	(17.2)	(5.2)	(16.0)	(4.6)	(11.1)
$CYCLE_M$	8.532	8.952	7.909	8.832	11.606
	(6.2)	(4.7)	(4.3)	(4.4)	(7.0)
$CYCLE_N$	7.190	8.027	6.120	5.672	8.819
	(5.1)	(3.7)	(3.3)	(3.3)	(5.5)
Individual traits:					
Hours worked per week	.011	.015	.010	.015	.010
	(33.6)	(24.9)	(24.8)	(25.0)	(24.9)
Education	.066	.063	.068	.063	.068
	(80.2)	(53.9)	(61.1)	(53.8)	(60.9)
Experience	.028	.029	.029	.029	.029
	(44.7)	(29.7)	(35.1)	(29.6)	(35.2)
Experience^2	−.0004	−.0004	−.00046	−.0004	−.00046
	(32.0)	(20.8)	(25.8)	(20.8)	(25.8)
Married (yes = 1)	.232	.180	.257	.180	.258
	(346.3)	(19.0)	(30.8)	(19.0)	(30.8)
Female (yes = 1)	−.195	−.242	−.174	−.242	−.174
	(26.0)	(19.7)	(18.5)	(19.8)	(18.4)
Married female (yes = 1)	−.270	−.223	−.293	−.223	−.293
	(28.6)	(14.8)	(24.4)	(14.8)	(24.4)
Nonwhite (yes = 1)	−.131	−.120	−.136	−.120	−.135
	(20.0)	(12.2)	(16.2)	(12.1)	(16.0)
Intercept	3.242	3.440	3.242	3.594	3.333
	(57.1)	(43.2)	(44.3)	(43.1)	(38.4)
Adjusted R^2	.4613	.5318	.4263	.5319	.4259

NOTE.—Absolute *t*-statistics in parentheses. All regressions include dummy variables for industry and year. See text for details.

probability of unemployment (regardless of the current stage of the business cycle).

To illustrate the effects of specialization on earnings, we used the results in column 1 of table 7. Recall that the standard deviation of specialization was .024 (see table 2). Each standard deviation increase in specialization increased weekly earnings by about 1.4% (.024 × .567). Our estimates indicate that weekly wages in the the five most specialized cities were 2.7% higher ([.182−.135] × .567), and wages in the five least specialized cities

Table 8
Log Weekly Wage Regressions, Further Results by CPS Subsample and Unique-Factor Variance

	All UVAR (1)	Manufacturing UVAR (2)	Nonmanufacturing UVAR (3)	Manufacturing $UVAR_M$ (4)	Nonmanufacturing $UVAR_N$ (5)
City traits:					
Unique-factor variance	3187.1	5095.8	3312.8	892.67	3366.5
	(2.3)	(2.5)	(1.8)	(2.9)	(.9)
Common-factor variance	94.644	98.006	82.829	13.876	−331.32
	(2.5)	(1.8)	(1.6)	(1.1)	(2.8)
Firm size	17.962	12.484	227.86	14.044	278.12
	(8.6)	(5.8)	(3.1)	(6.5)	(3.7)
City size	.016	.006	.020	.006	.016
	(16.6)	(4.5)	(15.7)	(4.7)	(11.2)
$CYCLE_M$	9.282	10.623	8.500	11.069	11.680
	(6.4)	(5.2)	(4.3)	(5.0)	(7.0)
$CYCLE_N$	8.979	7.607	8.785	6.367	8.973
	(7.1)	(3.8)	(5.3)	(3.7)	(5.7)
Adjusted R^2	.4612	.5319	.4261	.5319	.4259

NOTE.—All regressions include the same control variables as those reported in table 7.

were 1.8% lower ([.104−.135] × .567), than in otherwise identical cities of average specialization.

VII. Remarks

Our results indicate that individuals living in industrially more specialized cities faced a higher probability of unemployment, and earned higher wage rates as compensation. There are, however, several issues that need to be resolved.

First, we were puzzled by the negative effect of the nonmanufacturing common-factor variance, $CVAR_N$, on unemployment and wage rates. It would appear that $CVAR_N$ is a poor indicator of unemployment risk in the nonmanufacturing sector. What, then, could $CVAR_N$ be measuring? Perhaps supply-side factors (e.g., the increase in, and dynamics of, women's labor-force participation) may play a greater role in the nonmanufacturing sector.

A second issue is why the estimated effects of the unique-factor variances on unemployment and earnings were so much larger in magnitude than the effects of the common-factor variances. Although we have no direct evidence on this point, we conjecture that this is because the common-factor variances are dominated by the business cycle, which is transitory. Removing the transitory effects from employment fluctuations leaves the permanent component to be picked up by the unique factors. Employment risk is presumably greater when the fluctuations in employment are permanent; for example, a permanent layoff is more costly than a temporary layoff.[22]

A third issue is how our results fit into a world of implicit contracts that provide insurance for workers against fluctuations in the demand for their services. Many of the contract models are inconsistent with the finding of compensating wage differentials. Rosen (1985) considers an extreme case in which firms are risk neutral, provide severance pay, and insurance markets are perfect (pp. 1152–53). Firms with high demand would pay higher wages than firms with low demand, but there would be complete consumption insurance for workers. All employed workers would receive the same income, and all unemployed workers would receive the same income. Utility would be independent of the state of labor demand—laid-off workers would be as well off as employed workers (p. 1153). Clearly, compensating wage differentials for unemployment risk requires some degree of incompleteness in insurance markets (or risk-averse firms).

Insurance markets are likely to be incomplete when implicit contracts extend beyond one period. As pointed out by Rosen (p. 1171), a well-functioning labor market requires interfirm mobility: "A worker must bear some residual job finding risks because of the moral hazard effects of personal actions on success probabilities. . . . A contract must embody a delicate balance of encouraging mobility in response to permanent changes in demands and discouraging it for temporary shocks."

Holmstrom's (1983) article seems particularly relevant. In his model, the alternative job opportunities of workers play a significant role in the labor contract. "Outside labor opportunities act to reduce labor costs for firms in the same way as an exogeneous increase in unemployment insurance would. The strength of this effect will depend on the firm's relative riskiness, or in analogy with portfolio theory, its systematic risk" (p. 43). Holmstrom noted that whether such portfolio considerations were significant factors in determining wage levels was up to empirical testing. We feel that our study has taken another step toward answering this question in the affirmative.

VIII. Conclusions

Since the era of the classical economists, it has been hypothesized that specialization and trade are beneficial. Industrial specialization results in a lower cost of output for consumers. Yet industrial specialization has a

[22] Li's (1986) empirical results support this contention. She divided fluctuations in hours worked in an industry into cyclical and noncyclical components. Interindustry differences in cyclical unemployment risk accounted for an average $.61 difference in mean hourly wage rates, while interindustry differences in noncyclical unemployment risk accounted for a $1.56 difference in mean hourly wage rates (nn. 12 and 13, p. 291).

cost: it increases the risk of unemployment. In long-run equilibrium, labor is perfectly mobile between cities and must be compensated for above-average unemployment risk in the form of above-average wages. This article provides strong evidence in support of the compensating wage differential hypothesis. But firms, also, are mobile in the long run. That firms choose to locate in industrially specialized cities and pay higher wages provides important indirect evidence of the gains from industrial specialization.

Appendix A

Data Sources

Table A1
City-Level Variables and Data Sources

Variable	Description	Source
S_{ic}	1977 employment share of industry i in city c	*County Business Patterns* plus economic censuses*
HERF	Overall specialization	*County Business Patterns* plus economic censuses
HERF_k	Specialization in sector k, $k = M, N$	*County Business Patterns* plus economic censuses
E_{it}	National employment in industry i at time t	*National Income and Product Accounts*
de_{it}	Percent growth in industry i at time t, $= dE_{it}/E_{it}$	Authors' calculations (see text)
σ_{ij}	Covariance (de_{it}, de_{jt})	Authors' calculations (see text)
CVAR	Overall common-factor variance	Authors' calculations
UVAR	Overall unique-factor variance	Authors' calculations
CVAR_k	Common-factor variance in sector k, $k = M, N$	Authors' calculations
UVAR_k	Unique-factor variance in sector k, $k = M, N$	Authors' calculations
CYCLE_k	Cyclical index of demand in sector k, $k = M, N$	See Appendix B
FIRM SIZE	Average firm size by industry and city	*County Business Patterns*
CITY SIZE	1976 population in millions	*State and Metropolitan Area Data Book*, 1982.

SOURCES.—U.S. Bureau of the Census (1977*a*, 1977*b*, 1977*c*, 1979, 1982).
* The economic censuses include U.S. Bureau of the Census (1977*a*, 1977*b*, 1977*c*).

Appendix B

Construction of Cyclical Indicators

The indexes of cyclical demand fluctuations were computed using data on each city's industry employment shares and national industry growth rates. Let average monthly national employment in industry i in year t equal E_{it} ($i = 1, \ldots, 28$; $t = 1977, 1978, 1979$). The percent growth in average monthly employment in year t is $de_{it} = \log(E_{it}/E_{it-1})$.

There were 22 manufacturing industries (including agriculture and mining) and six nonmanufacturing industries. Recall that employment in industry i in city c is given by E_{ic}. Denote E_{Mc}, E_{Nc}, and E_c as manufacturing, nonmanufacturing, and total employment in city c. The weighted cyclical demand fluctuation indexes for manufacturing and nonmanufacturing were defined as

$$\text{CYCLE}_{Mct} = SM_c \sum_{i=1}^{22} SM_{ic} de_{it}$$

and

$$\text{CYCLE}_{Nct} = SN_c \sum_{i=1}^{6} SN_{ic} de_{it},$$

where

$$SM_{ic} = E_{ic}/E_{Mc};$$

$$\sum_{i=1}^{22} SM_{ic} = 1;$$

$$SN_{ic} = E_{ic}/E_{Nc};$$

$$\sum_{i=1}^{6} SN_{ic} = 1;$$

$$S_{Mc} = E_{Mc}/E_c;$$

$$S_{Nc} = E_{Nc}/E_c;$$

and

$$S_{Mc} + S_{Nc} = 1.$$

CYCLE_{Mct} and CYCLE_{Nct} were merged by city and year with the individual CPS data.

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