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Efficiency of Resource Usage and City Size*

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INTRODUCTION

This paper estimates the nature and extent of external economies of scale in two-digit manufacturing industries. Cross-sectional data for the United States and Brazil are utilized, with urban areas as the unit of observation. The econometric work provides important evidence toward resolving major questions in the literature on scale economies, industrial location, and urban economics in general. In this literature, parametric external economies of scale are the accepted basis for the existence of large cities (Mills, 1967; Dixit, 1973; Henderson, 1974), with competitive production sectors (Chipman, 1970). The first question is whether these external scale economies are ones of localization or of urbanization. A second question is whether these scale effects are large and persist, or whether they tend quickly to peter out. The answers to these questions have implications for questions concerning the nature of a system of cities, industrial location, and the efficiency of big versus small cities.

Nature of External Economies of Scale

Urban external economies of scale arise from placing relevant resources in spatial proximity such as the same city, which improves the productive environment of local firms. A basic question concerns the nature of these scale economies, or what characterizes the external environment relevant to a firm's productivity. One answer is that external economies of scale are ones of localization, indicating that they are internal to each industry in a particular city. Thus, the scale factor affecting a firm is measured by total employment (or output) in that firm's industry in that urban area. These economies reflect (i) economies of intraindustry specialization where greater industry size permits greater specialization among firms in their detailed functions, (ii) labor market economies where industry size reduces search

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costs for firms looking for workers with specific training relevant to that industry,[1] (iii) scale for "communication" among firms affecting the speed of, say, adoption of new innovations, and (iv) scale in providing (unmeasured) public intermediate inputs tailored to the technical needs of a *particular* industry.

An alternative answer is that scale economies are urbanization ones, which means they are external to any industry, and result from the general level of economic activity in a city, as might be measured by total city population or employment. These economies reflect benefits of operating in a large urban environment where there is a large overall labor market, a large service sector interacting with all manufacturing, and so on. While different industries might experience different degrees of urbanization economies, only the size of the city, not its industry composition, affects the extent or level of scale effects relevant to firms in each industry.

Implications for Industrial Location

What are the implications of whether scale economies are primarily ones of localization or of urbanization? First, there is the issue examined by Moomaw (1981), Segal (1976), and Sveikauskas (1975) of whether production resources are more efficient in large versus small cities. On an aggregative level, resources are in some sense more productive in large cities—otherwise large cities with their high costs of living could not pay the high wages necessary to attract residents. The question is why this occurs. One answer is that generally economies of scale are urbanization, implying that all types of resource employment are more efficient in large cities. This notion, however, can raise the question of how small cities then manage to exist, attract resources, and thrive. An alternative answer is that large cities are more productive both because they have different industrial compositions and because economies of scale are localization. Small cities contain industries with low localization economies while large cities contain ones with high localization economies.

Note that these notions imply that it is critical to estimate the nature of scale economies industry by industry, rather than to specify an aggregate production function for the city (where an aggregate function also involves mixing different technologies which makes it difficult to interpret any estimates). An aggregate production function can by definition have only urbanization economies represented in it. There is then no way of determining whether the resulting urbanization measures capture only industrial composition effects, where as we move up the city size distribution, industry composition is shifting toward industries with greater localization economies. Our empirical results suggest that this is what happens.

[1] Note that these are real not pecuniary externalities, as modeled in the search literature.

The nature of scale economies has related implications for industrial location. If scale economies arise primarily from localization benefits, then simple theoretical models suggest that the monocentric cities of the urban literature tend to completely specialize in production of goods which are traded across cities (Henderson, 1974, 1983).[2] In these models, equilibrium is characterized by different types of cities, where each type is specialized in the production of one set of interrelated export goods. Different types of cities have different equilibrium sizes, increasing as the degree of localization economies of the industry the city is specialized in increase. In that case, the relevant question is not whether resources are more productive in large versus small cities, but what types of industries are best off (and likely to be found) in what sizes of cities.

In the empirical work we will point out a strong correlation between industries which exhibit localization economies and industries which cities tend to specialize in. Thus, it is important to clarify what we mean by specialization and to note which industries cities tend to specialize in.

In practical application considering, for example, transport costs, the notion of absolute specialization becomes to some extent one of relative specialization. First, even in the absence of urbanization economies, certain footloose industries which otherwise might each form the core of specialized separate monocentric cities, may cluster together to reduce the intercity costs of trade and form large multinucleated metropolitan areas.[3] Second, while some urban areas may specialize in the export of one two- or three-digit product, some others may produce expensive-to-transport components of that product primarily for local consumption. From uncensored three-digit Industrial Census data for Brazil there appear for many industries to be three classes of urban areas.[4] For any two-digit industry, at least half (textiles and food processing) and often three-quarters or more (machinery and metals) of the urban areas have no employment in any (three- or four-digit) component of that industry. The remaining cities that have employment in that industry tend to form a bimodal distribution with about three-quarters having minimal employment, typically in four-digit

[2] With urbanization economies, specialization may also occur if the degree of urbanization economies varies across industries. However, in this case the forces for specialization are much weaker than with localization economies when intercity transport costs (see later) are introduced.

[3] See Henderson [1983] for a discussion of this process allowing for resource-using and footloose industries. Note that natural resource considerations can help explain some degree of specialization. However, many of our specialized types of cities (see Appendix A) are not resource intensive. Second, if scale economies are ones of urbanization, there is no reason why footloose industries will not be attracted to cities which have resource-using production.

[4] Due to censoring for disclosure, we cannot do this classification for the United States based on Manufacturing Census Data.

parts or repair subcategories, and one-quarter having large employment in one three-digit component.

To what extent is the notion of specialization consistent with the data? At least half of the 243 U.S. SMSA's in 1970 could be classified as highly specialized in one manufacturing industry. The same comment applies to the 126 urban areas in our Brazilian sample.[5] For the U.S., in Appendix A, we present a sample of results from applying cluster analysis to form groups of SMSA's with similar proportions of employment for 229 industries. Using a strict cluster criterion in the algorithm, the following types of manufacturing SMSA's are identified: auto (12 SMSA's), aircraft (6), shipbuilding (4), steel (9), industrial machinery (5), communication equipment (4), petrochemicals (4), textiles (6), apparel (7), leather products (3), pulp and paper (6), and food processing (5). Where possible, the fraction (lower bound estimates) of local employment in an industry is noted. Anything beyond 20% is a very narrow SMSA, given that the bulk of local employment is in nontraded good employment (local government, housing, retail, and personal services, etc.). Moreover, specialization is so pervasive that most SMSA's have strong representations in only a few of the 117 manufacturing categories represented in the most detailed population Census data.

SMSA's not specialized in manufacturing generally fall into three categories: large diversified megopolises (consisting of multiple-name SMSA's representing agglomerations by the Census Bureau of formerly independent SMSA's), government urban areas (state capitals, university towns, etc.), and cities servicing rural areas in a traditional central place model (with heavy employment concentrations in wholesaling, warehousing, and transportation). In general, the largest megopolises are underrepresented in heavy manufacturing.

Focus of the Paper

The econometric work in the paper deals with the following questions. Are scale economies urbanization or localization ones? Does the degree of scale effects (defined later) remain constant, increase, or peter out as the level of scale increases? Do industries where scale effects are localization ones tend to be the dominant industries of specialized cities?

To answer these questions we use both Brazilian and U.S. samples described later. The samples complement each other, in that certain tests

[5] For Brazil from eyeballing employment patterns, we found the following types of cities: textiles (22 urban areas), apparel (1), iron and steel (6), food processing (10), nonmetallic minerals (5), pulp and paper (2), transport equipment (2), chemicals (1), beverages (1), and nonelectrical machinery (2). Specialized urban areas have 9–49% of employment in just one usually three- or four-digit industry, with a typical concentration of 20%.

which cannot be carried out in one sample can be carried out in the other, given differing data availability. The use of different samples also allows us to point out the cross-country consistency in findings about the nature of systems of cities.

The only closely related attempt we know of to examine urban external economies of scale is Sveikauskas (1975, 1978). The questions Sveikauskas focuses on are somewhat different; and in measuring productivity, he is unable to control for variations in factor ratios and in labor force qualities across cities. However, some of his results are similar to ours (see especially Sveikauskas, 1978, Table 9) where he estimates significant localization economies for food, apparel, transport equipment, machinery, electrical machinery, and to some extent primary metals). Shefer (1973) and Carlino (1978) have also examined sources of scale effects, but their results are inferred from a restrictive interpretation of the impact of scale effects on a CES production function. In contrast, we opt for a flexible functional form approach in estimating urban productivity; and we estimate scale effects directly, controlling for other arguments affecting productivity. Hansen [1983] also examines productivity by firms in Brazil and concludes that for his special sample neither urbanization nor localization economies are important. However, his results are not generalizable and his data are inadequate to draw conclusions concerning urban agglomeration effects.

1. METHODOLOGY FOR MEASURING THE NATURE AND EXTENT OF EXTERNAL ECONOMIES OF SCALE

1.1. Sources and Magnitudes of Scale Effects

To estimate the nature and extent of scale effects, we define two general approaches. For Brazil, we employ versions of both approaches to check that they yield the same results. For the U.S., we have the data only for the second approach.

Approaches to Specifying Technology

The first approach is to estimate a production function where

$$Y = g(\mathbf{S})\tilde{Y}(\mathbf{K}). \tag{1}$$

$\tilde{Y}(\mathbf{K})$ is the firm's own CRS technology for $\mathbf{K}$ a vector of inputs. $g(\mathbf{S})$ is a Hick's neutral external shift factor whose arguments are scale and technology measures specific to an industry in an urban area. Since $\tilde{Y}(\cdot)$ is CRS, we can aggregate over firms and use industry-urban area observations. The assumptions of Hicks' neutrality and CRS are tested below.

Equation (1) may be rewritten as $Y/L = g(\mathbf{S})Y(\mathbf{k})$ where L is labor inputs and k the vector of ratios of remaining factors to L. Taking logarithms, defining $\log(Y(\mathbf{k})) = f(\log \mathbf{k})$ and doing a second-order Taylor series expansion of $f(\cdot)$ about all $k_i = 1$, we get a translog type of specification for the estimating equation

$$\log(Y/L) = C_0 + \log g(\mathbf{S}) + \sum_i \alpha_i \ln k_i + 1/2 \sum_i \sum_j \gamma_{ij} (\log(k_i))(\log(k_j)). \tag{2}$$

To infer scale effects, we estimate (2) rather than a traditional multiequation model with a primary production function (1) plus factor share equations. The factor share equations provide no direct information about $g(\mathbf{S})$ and estimates of the primary production equation are subject to multicollinearity which (2) avoids.[6] Two attempts to construct the necessary data to estimate a translog production model for the U.S. yielded estimates that violated basic regularity conditions. Since we are focusing on scale effects, not on elasticities of substitution, we chose (2) as the approach.

The second approach we employ is to define the unit cost function consistent with (1) and the Hicks' neutrality and CRS assumptions where unit costs, c, are

$$c = (g(\mathbf{S}))^{-1} c(\mathbf{p}) \tag{3}$$

for $\mathbf{p}$ a vector of input prices and $c(\cdot)$ the dual representation of the firm's CRS technology. $g(\cdot)$ is the same as that in Eqs. (1) and (2). From Shephard's lemma, $\partial c/\partial p_L = L/Y$, where L is the labor input and p_L its price.

Taking the reciprocal and then logs, we get

$$\log(Y/L) = \log g(\mathbf{S}) + \log\left((\partial c/\partial p_L)^{-1}\right). \tag{4}$$

We call (4) the dual factor usage equation. Again in the spirit of the translog approach, we define the second term on the RHS of (4) to be a function $\phi(\log p_i)$. We approximate it by a first-order Taylor series expansion about $p_i = 1$. Given that (4) is already a differentiated function, we did not add in the second-order terms in presenting the results. Experimentation indicated little gain from doing so (see footnote 9). Thus

$$\log(Y/L) = C_1 + \log g(\mathbf{S}) + \sum_i a_i \log p_i. \tag{5}$$

[6] For example, for Brazilian machinery, iron and steel, and electrical machinery, and for U.S. fabricated metals and machinery (where capital stocks for 55–60 SMSA's were laboriously calculated from investment series), the simple correlation coefficients between *any* pair of output, labor, and capital stock were *over* 0.95 in every case.

In (5), while the a_i in theory could be used to calculate typical measures of technology (e.g., variable partial elasticities of substitution), in our work, because of data limitations, the measures are not identifiable. For the same reason we do not estimate a full cost function and factor share equation model. The specification of (5) is discussed again later.

Specification of Scale Effects

The scale measures in (1)–(5) relate to measures of localization and urbanization economies. The former are measured by own industry employment in an urban area and the latter by either urban area population or total local employment (the results are identical). We experimented in both samples with various specifications for scale effects. In both cases, the experiments described later strongly indicated that generally the best specification was

$$g(\cdot) = e^{\gamma/L} N^{\varepsilon_N} \tag{6}$$

where

$$\varepsilon_L = d(\log Y)/d(\log L) = -\gamma/L.$$

L is own industry employment in an urban area and N is the population of the urban area. The interpretation of the ε_L and ε_N elasticities is that a 1% increase in, respectively, L or N leads to a ε_L or ε_N% increase in output of any firm in the industry in the urban area, *holding the firm's inputs fixed*. The specification of a declining ε_L is strongly supported by evidence presented later. It also has the advantage of reducing collinearity between the scale measures. We also experimented with some other external scale economy measures noted later.

Control for Other Effects

Usable technology for an industry in the sense of what production innovations firms adopt may vary across SMSA's as the education and experience of the industry labor force varies. To control for this and other impacts of labor force quality, we insert measures of age and educational attainment *specific to an industry in an urban area* (as arguments of $g(\mathbf{S})$).

In (1), $\tilde{Y}(\cdot)$ may not be homogeneous of degree one. To allow for degrees of homogeneity different from one, we control for average firm size for each industry in each urban area. While this is a direct test of the degree of homogeneity, it is not a direct test of the assumption that $\tilde{Y}(\cdot)$ is homogeneous of some degree, an assumption which allows us to aggregate across firms. A significant coefficient for average firm size under our assumptions measuring a degree of homogeneity different from one would also raise a suspicion of general nonhomogeneity.

Finally, we note that scale effects may not be Hicks' neutral. The tests of Hicks' neutrality and the results confirming neutrality are discussed later.

1.2. Empirical Implementation

Statistical Problems

The problems in estimating (2) and (5) are related and we discuss (2) first. In estimating (2), factor ratios and the measures of own industry scale could be viewed as endogenous variables whose magnitudes are subject to disturbances correlated with disturbances in (2). Ordinarily a remedy would be to use 2SLS with factor prices and urban population treated as exogenous variables and used as instruments.

Unfortunately, our situation is not a traditional one. For many industries, in some urban areas the industry is the dominant export industry of the city. In any theoretical model [e.g., Mills, 1967] this means own industry employment, local wage rates, taxes, and city population are jointly determined. Thus factor prices and city populations may not be suitable instruments. For Brazil, there was simply not enough other information on cities to provide a list of suitable other instruments to test for proper specification or to do 2SLS work. For the U.S. in estimating (5) we also have the same problem of endogenous RHS variables such as wages, labor force quality, and scale measures. Here we had a long list of possible instruments. We do Hausman [1978] specification tests for orthogonality of explanatory variables to the error term and we report 2SLS results for the U.S.

Data

For the U.S. the primary data source is the 1972 Census of Manufacturers. Labor force quality measures and demographic information were obtained by utilizing tables from the Sixth Count of the 1970 Population Census, accounting for major changes in SMSA definitions between 1970 and 1972. The basic sample covers 238 SMSA's. Details of variable definitions and other data sources are given in Appendix B.

For Brazil, the primary data source is the 1970 Industrial Census. The data are remarkable. Included are data on different taxes, wage supplements and fringes, and current market values of equipment and structures. Industry specific labor force quality measures were obtained from the 1970 Demographic Census. Details are in Appendix C. The basic sample is the 126 urban areas over 20,000 in 1970 in Southern Brazil (the states of Minas Gerais, Espirito Santo, Rio de Janeiro, Sao Paulo, Santa Catarina, and Rio Grande do Sol). Southern Brazil is the large well-developed region of Brazil containing major cities on the coast and in the resource-rich interior, all interconnected by modern transport and communication services. The system of cities is similar to that in the U.S. in terms of specialized cities, size distribution, and the stability of that distribution. The urban area definition in Brazil is similar to the U.S. SMSA definition. Counties (municipios) are grouped together to form urban areas for large urban areas and smaller urban areas are a single county (municipio).

Specifics of Estimating Equations

For the U.S. we estimate the dual factor usage equation (5), where output is measured by the value of production (the now preferred alternative to value added [Fuss and McFadden, 1978]). The corresponding relevant input prices on the RHS of (5) are wages p_L, capital costs, and materials costs. For the last two prices we have no data. We could assume that these prices are spatially invariant, apart from a random component. However, the location theory literature is predicated on the presumption that gross materials prices vary across space in a consistent fashion with distance from regional market centers. Moreover, the notion of transport cost delineated market areas is consistent with evidence [Weiss, 1972]. Therefore, we allow materials price to vary by distance u from regional market centers, so that price is $p_0(1 + bu)$ for p_0 the price in regional market centers. The sign of b is not restricted.[7] In estimation, $\log[p_0(1 + bu)]$ is approximated by $\log p_0 + bu$. Second, three regional dummy variables (RD_i) are inserted to allow for regional market center price (p_0) differences relative to the Northeast. The regional dummies also may capture regional differences in the cost of capital. Thus, (5) is revised to become

$$\log(Y/L) = \log G(\mathrm{S}) + A_0 + \beta_1 \ln p_L + \beta_2 u + \sum_{i=1}^{3} \delta_i \mathrm{RD}_i. \qquad (5a)$$

The flexible function form approach inherent in (5a) allows us to directly estimate the characteristics of $G(\mathrm{S})$ without having to interpret them under the restriction that technology is precisely represented by one particular specific functional form. However, if we drop the terms in (5a) beyond $\ln p_L$, this truncated form of (5a) is the same as a factor productivity equation based on a CES production function. Like Sveikauskas [1975, 1978] or Hansen [1983] we do not interpret our results in the context of a CES function, but utilize the direct flexible functional form interpretation of (5a), or even any truncated form of (5a). There are three reasons for doing so. The extensive econometric work of the last decade or so on production technology has decisively rejected most traditional specific functional forms, in particular the conventional CES (see Fuss and McFadden [1979] for a review). Second, our statistical work supports this rejection and indicates

[7] That is, some raw materials may be more expensive in market centers than near their hinterland source.

that the terms beyond $\ln p_L$ in (5a) are generally significant (and so can be additional second-order terms).[8] Finally and perhaps most critically, in the Brazil work where both (2) and (5) can be estimated, our two sets of results (production function and dual factor usage equation) for the form of the $\log G(\mathbf{S})$ function are almost *identical* under the flexible functional form interpretation of (5a), but *radically* different under, say, a CES interpreta- tion of a truncated (5a), where a CES is "unstable" for elasticities of substitution near 1.[9]

[8] By comparing estimates of (5a) with and without all terms beyond $\log p_L$, one can perform a rough single-equation test of the validity of the CES. An F test rejects the truncated (CES) version in 8 out of 16 industries at the 0.05 level, 2 more at the 0.10 level, and another 2 at the 0.20 level. We also tested the truncated (CES) version against a second-order Taylor series expansion of (4), which adds $(\log p_L)^2$, u^2, and $\log p_L^* u$ to (5a). All but 3 industries reject the truncated version at a 0.20 level (and 9 reject it at a 0.05 level). Two of those three industries are printing and furniture which are not important industries in our analysis. As an aside, we note that in testing a second-order Taylor series expansion against a first, only 7 out of 16 industries accepted the expanded version of the 0.20 level, and just 3 at a 0.05 level. To reduce the level of "noise" in the equations we use just the first-order expansion. The impact on the scale effects is minimal. In 10 industries γ changes by less than 5%. In only 3 industries are there big changes (over 20%), and in only 1 of those (leather products) are the coefficients reasonably significant to begin with. For the sake of comparison, for 3 industries we present the results on critical variables in (i) (5a) and in (ii) the truncated (CES) version of (5a):

		$1/L$	$\ln N$	$\ln p_L$	u	Reg NC	Reg S	Reg W	adj R^2
Food products	(i)	−1.01	−.01	1.14	.02	.26	.13	.13	.40
		(2.78)	(.50)	(7.48)	(2.98)	(4.21)	(2.08)	(1.83)	
	(ii)	−1.24	−.04	1.11					.32
		(3.28)	(1.90)	(7.84)					
Pulp and paper	(i)	−.46	−.02	1.03	.02	.02	.05	.14	.60
		(2.15)	(1.27)	(7.13)	(2.11)	(.33)	(1.02)	(2.05)	
	(ii)	−.49	−.03	1.06					.57
		(2.24)	(1.78)	(7.87)					
Machinery	(i)	−.67	.003	.49	.01	.10	.03	.10	.31
		(2.56)	(.20)	(3.45)	(2.08)	(2.57)	(.68)	(1.73)	
	(ii)	−.72	−.01	.48					.27
		(2.43)	(.67)	(4.11)					

[9] In a CES the estimates of scale effects are obtained by combining the estimates of $G(\mathrm{S})$, with the coefficient of $\log p_L$, where as the coefficient of $\log p_L$ (the elasticity of substitution) approaches 1, the equation exhibits "instability" and there is a sign switch in the interpretation of scale effects. For example, a coefficient of 0.1 on $\ln N$ is interpreted as a positive scale elasticity of 10 if the point estimate of the coefficient of $\ln p_L$ is 0.99 and a negative scale elasticity of −10 if the point estimate of the coefficient of $\ln p_L$ is 1.01. We interpret the elasticity directly stating that a 1% increase in N will raise productivity by 0.1%. For the first six industries in Table 1 (RHS), the estimates of γ under a CES interpretation would be iron and steel 375, machinery −43, transport −91, chemicals −305, textiles 224, food −240. As we will see later, four of these six results are radically different (including two sign switches) from the production function results. In contrast a flexible functional form interpretation of (5a) yields in all cases results that are statistically indistinguishable from the production function results.

For Brazil, in estimating (2) and (5a), output is measured by value added because we did not have a good measure of value of production.[10] For value added, inputs are capital and labor. In estimating (2) inclusion of both the $\log k$ and $(\log k)^2$ terms resulted with one exception in insignificant $(\log k)^2$ terms, and thus $(\log k)^2$ is generally dropped. In essence, in Brazil with the smaller sample sizes, the data only permit us to approximate technology by a first-order Taylor series expansion—a Cobb–Douglas function. In (2) and (5a) for Brazil, despite the absence of materials we leave in the distance terms. In the Brazilian institutional context, in (5) the distance term allows for capital market imperfections where the price of capital rises with distance from major market centers, in the absence of other information on overall capital costs. Second, inclusion of the distance terms in the context of a less developed country to control for possible variations in output prices seems reasonable.

2. EMPIRICAL RESULTS

In presenting the empirical results, we start with the results on external economies of scale. We first present the primary, OLS results for two-digit industries, for Brazil, and then for the U.S. Then we present 2SLS results for the U.S. and results from experimenting with the functional form specification of scale effects. Finally, we examine other possible sources of external economies of scale. Having completed the examination of scale effects we turn to results on other variables in the basic OLS versions of (2) and (5) for two-digit industries for the U.S. and Brazil. We conclude this section with an examination of whether scale effects are Hicks' neutral.

2.1. External Economy of Scale Estimates

We start with Brazil to demonstrate the consistency of results obtained from the production (2) and dual factor usage (5) equations. We then turn to the results for the dual factor usage equation for the United States.

Brazil

In this section in Table 1 we present results for Brazil for (2) and (5) for the component $\log g(S) = -\gamma/L + \varepsilon_N \log N$. Note that for positive locali- zation economies $\gamma < 0$ and $\varepsilon_L = -\gamma/L$. On the LHS of the table are the production function (2) results and on the RHS the factor usage (5) results. The RHS results were obtained early in the project for (only) the sample of industries shown and since the production function became the primary

[10] There was a problem both with the materials data and with inclusion of home production.

equation only it covers all industries. All two-digit industries with sufficient sample size are represented for the production function.[11]

Examining the estimates of ϵ_N from the production function, there is almost no evidence of urbanization economies except in printing and publishing and some weak evidence for nonmetallic minerals and furniture. For the other industries, sign patterns are mixed and coefficients hover near zero.

In contrast is the strong evidence of localization economies. Except for printing, all γ coefficients are negative and hence all scale elasticities positive. Given the multicollinearity between L, log N, and firm size, most of the coefficients of $1/L$ are significant at a reasonable level. We also reestimated the production equations dropping the log(N) term where it had a trivial impact (arbitrarily defined as both a coefficient under 0.03 and a t statistic under 0.75). These results are reported in square brackets in Table 1, beside the first column of figures. Dropping log(N) has little impact on the γ coefficients; however, in all but one case t statistics are raised.

The localization effects are large. Median employment across urban areas for most industries in the sample is 350–500 employees, although for iron and steel and textiles it is nearer 900. Evaluating the elasticities at 500 employees yields the figures in the second main column. The numbers are typically over 0.1, meaning that at 500 own industry workers in a city, a 10% increase in own industry employment in the city will cause a firm's output to rise by 1% without the firm increasing its own inputs. Put in a different light, a 10% increase in industry employment will allow the industry (for the same cost of capital) to raise wages by $1/\alpha\%$, where α is labor's share in a Cobb–Douglas production function.

Finally, for Brazil, from the RHS of Table 1, the estimates of external economies of scale based on the dual factor usage equation are very close to those for the production function. This was most encouraging because for the United States we had to rely on only the dual factor usage equation. We turn to the U.S. results now.

[11] For Brazil there is a problem that the repair and other servicing activities associated with an industry are put in the manufacturing sector, not the service sector. To avoid having observations where there was only a service component in the urban area, we excluded observations where employment fell below 100 in the urban area from the beginning (also two-digit industries but not three-digit were censored). Note that in the U.S., data observations where employment is only 100 almost never appear — they are automatically censored out. In later work focusing on elasticities of substitution using a translog equation system for detailed three-digit industry data where activities are more homogeneous, we included all observations. The localization versus urbanization results were just as strong, although a quadratic formulation for localization economies became dominant.

TABLE 1

External Scale Effects for Brazil: Two-Digit Industries

	Production function equation[a]					Factor usage equation[b]	
	γ		ϵ_L $(= -\gamma/500)$	ϵ_N	N	γ	ϵ_N
Iron and steel	−101.233	[−93.721]	.20	−.021	36	−109.49	−.036
	(1.79)	[(1.94)]		(.26)		(2.30)	(.57)
Nonelectrical machinery	−36.100	[−43.749]	.07	.027	57	−28.00	.015
	(1.85)	[(2.71)]		(.71)		(1.39)	(.34)
Transport equip.	−69.885	[65.616]	.14	.009	26	−69.80	−.003
	(2.43)	[(1.97)]		(.20)		(2.04)	(.05)
Chemicals	−103.657		.21	.084	28	−128.26	.017
	(2.59)			(1.28)		(2.10)	(.15)
Textiles	−60.273	[−57.812]	.12	−.010	58	−64.88	.004
	(1.54)	[(1.57)]		(.20)		(1.93)	(.09)
Apparel	−15.992	[−22.797]	.03	.018	42		
	(.49)	[(.92)]		(.23)			
Pulp and paper	−65.958	[−65.259]	.13	.005	21		
	(1.32)	[(1.51)]		(.06)			
Food processing	−21.586		.04	−.038	107	−36.136	−.060
	(.78)			(.76)		(1.53)	(1.31)
Nonmetallic minerals	−27.941		.06	.080	75	−36.852	.066
	(1.00)			(1.33)		(1.86)	(.14)
Furniture	−24.066		.05	.049	53	−37.406	.020
	(1.13)			(1.15)		(1.67)	(.42)
Printing & publishing	9.461			.177	32	−25.302	.180
	(.36)			(3.56)		(1.16)	(2.88)

Note. t statistics are in parentheses.

[a] The basic estimating equation is (variable definitions are in Appendix C) $\ln(Y/L) = f(1/L, \ln(N)$, ln (average fs), u, ln (k), average age, percent $1f$ illiterate). For industries with less than 35 observations, average age, percent $1f$ illiterate, and u are dropped.

[b] The estimating equation is Eq. (5a) without regional dummies (given only one region in the Brazilian sample).

United States

On the LHS of Table 2, we present the OLS results on external economies of scale for the United States.[12] For the United States only nonmetallic minerals has significant positive urbanization effects. For the remaining industries there is an almost equal division between positive and negative urbanization effects.

[12] The transport industry is omitted because censoring removes almost all important data points. Two-digit industries 38 and 39 are omitted on the basis that they are simply groupings of miscellaneous activities. Tobacco is omitted because the sample size is only four.

TABLE 2

External Scale Effects for the U.S.: Two-Digit Industries

	OLS			2SLS		
	α	ε_N	$\varepsilon_L(=\alpha/5)$	α	ε_N	N
Primary metals	1.201	.073	.24	1.627	.088	98
	(2.12)	(1.96)		(1.57)	(1.78)	
Electrical machinery	1.087	.022	.20	1.411	.025	110
	(2.84)	(1.07)		(2.12)	(.68)	
Machinery	.673	.033	.13	.33	.020	168
	(2.56)	(.20)		(.43)	(.69)	
Petroleum	2.226	.302	.45	1.985	.366	36
	(2.50)	(3.26)		(1.79)	(3.27)	
Apparel	.665	.055	.13	2.226	.050	70
	(.97)	(1.58)		(2.23)	(.88)	
Textiles	.042	−.036	-	1.648	.070	64
	(.07)	(1.06)		(1.25)	(1.36)	
Leather products	.695	.016	.14	1.047	.030	37
	(1.47)	(.58)		(1.71)	(.96)	
Wood products	.542	.025	.11	.791	.041	128
	(1.93)	(1.21)		(1.19)	(1.26)	
Pulp and paper	.460	.021	.09	.879	.038	105
	(2.15)	(1.27)		(1.14)	(1.13)	
Food products	1.007	.013	.20	2.063	−.047	211
	(2.78)	(.56)		(2.11)	(1.09)	
Publishing and printing	−.120	.013		.326	.009	210
	(.65)	(.73)		(.62)	(.25)	
Furniture	.441	.022		.030	.005	95
	(1.89)	(1.05)		(.06)	(.14)	
Fabricated metals	.179	.028		.424	.006	185
	(.71)	(1.58)		(.68)	(2.43)	
Nonmetallic minerals	.859	.074		.398	.092	164
	(4.50)	(4.00)		(.60)	(2.50)	
Rubber	.293	.004		.005	−.016	97
	(.89)	(.17)		(.01)	(.45)	
Chemicals	.739	.022		1.357	.062	125
	(2.29)	(.72)		(1.11)	(.93)	

In contrast, except for textiles, for the top panel of industries localization economies are strong and generally significant. The localization elasticities are also somewhat larger than the Brazilian numbers as evaluated at the same point (500 employees). However, median U.S. employment in any industry across the sample of SMSA's is typically near 2500 employees, so that elasticities evaluated near the median are much smaller.

Allowing for differences in industry definitions and coverage, similar industries do or do not exhibit strong localization effects in the United States and Brazil. Similar patterns of strong localization effects hold for the heavy manufacturing industries in the first three or four rows of Tables 1 and 2. (In Brazil the chemical industry includes petrochemicals which have strong localization effects in the United States.) The lighter manufacturing industries which urban areas specialize in (leather products, wood products, pulp and paper, food products) also demonstrate strong localization effects, especially in the United States (apart from textiles in OLS estimates).

In both countries there is a strong general relationship between industries which cities specialize in and industries having localization economies. For example, for the United States, the top panel of industries are all ones which SMSA's specialize in.[13] In contrast, in the bottom panel, the more ubiquitous consumer industries (printing, nonmetallic minerals) or ones found in many cities often mostly servicing local manufacturers with intermediate inputs (fabricated metals) exhibit either no localization effects or even negative ones.

On the RHS of Table 2, we present 2SLS results. Before doing 2SLS, we did simple specification tests in Hausman [1978] to test for orthogonality of the explanatory variables to the error term for industries where we thought this would potentially present a problem (that is, we focused on industries which cities specialize in such as food products, textiles, apparel, leather products, wood products, pulp and paper, primary metals, machinery, and electrical machinery). Strong evidence of nonorthogonality for any variables (including $1/L$) exists only in food products, textiles, and apparel.[14] Any evidence of nonorthogonality in these other industries was weak, although at times the power of the tests appeared also very weak [Hausman, 1978, p. 1260]. The 2SLS estimates do treat wages, population, industry employment, and labor force quality measures as endogenous for all industries. However, only for food products, textiles, and apparel is there good a priori evidence that the 2SLS estimates will be an improvement over OLS.

Indeed, in Table 2, with one exception, the industries experiencing the biggest impact of switching to 2SLS are food products, textiles, and apparel, which go from displaying moderate or negligible localization economies to very strong effects. In general, in the 2SLS work localization effects are strengthened, at least numerically, while evidence for positive urbanization effects is weakened. The exception is machinery, which did not display

[13] From footnote 5, the same comment applies to Brazil.

[14] The basic specification we used was $y = X_1\beta_1 + X_2\beta_2 + \hat{X}_1\alpha + \varepsilon$, where X_1 are potentially nonorthogonal to ε. We also compared OLS and 2SLS estimates, according to the procedure in Hausman [1978; footnote 9]. The tests have a low power if $\hat{\alpha}$ and its standard error are both large.

strong evidence of nonorthogonality, and thus may illustrate the dangers (loss of information) inherent in 2SLS work. Given the difficulty in obtaining instruments for doing 2SLS work and the uncertainty about nonorthogonality from the poor power of the tests for many industries, we conclude that only for textiles, food products, and apparel are the OLS estimates inappropriate.

Any statistical exercises which we did followed a pattern of either strengthening localization effects at the expense of urbanization ones or maintaining the same patterns as in Table 2. These exercises included Ridge regression work and the use of nonflexible functional form equations such as Hanoch's CRESH (which had poor global properties).

2.2. Specification of Localization Economies

In Tables 1 and 2, elasticities of localization are specified to be declining. This specification was chosen for two reasons. First, relative to a constant elasticity, it generally yielded a noticeably lower standard error of estimate (60% of the time) and rarely a noticeably higher one. Finally, and most critically, the declining elasticity form in both samples was strongly supported, as footnoted for the United States, by a quadratic specification of the form[15]

$$\log g(S) = \alpha \log L + \beta(\log L)^2 + \varepsilon_N \log N.$$

We prefer the simpler declining elasticity form to the quadratic because of its global properties and attractiveness for use in theoretical modeling or simulation, as well as the reduction in multicollinearity. In general, the elasticities from the quadratic form are larger at median employment but in industries where both terms of the quadratic are statistically strong by mean employment they are similar or even lower for the quadratic.

We also note that constant elasticity estimates are similar to declining elasticity estimates evaluated at median employment. The few exceptions are industries which exhibit a very high degree of collinearity between log L and log N.[16]

[15] For primary metals, electrical machinery, machinery, petroleum, *apparel*, leather products, wood products, pulp and paper, and food products, respectively, the pairs of values of α and β and their t statistics in parentheses are ⟨0.28 (2.14), 0.030 (1.72)⟩; ⟨0.190 (2.34), −0.020 (2.01)⟩; ⟨0.094 (1.61), 0.006 (0.80)⟩; ⟨1.228 (3.00), 0.181 (2.60)⟩; ⟨0.155 (1.67), −0.006 (1.16)⟩; ⟨0.334 (2.15), 0.044 (1.89)⟩; ⟨0.173 (1.46), 0.023 (1.09)⟩; ⟨0.067 (0.97), −0.002 (0.22)⟩; and ⟨0.161 (1.76), 0.014 (1.03)⟩. The corresponding ε_L's ($= \alpha + 2\beta \log L$) evaluated at median employment are 0.077, 0.041, 0.052, 0.327, 0.107, 0.079, 0.067, 0.055, and 0.077.

[16] These are the more ubiquitous industries in the United States of food, printing, nonmetallic minerals, and fabricated metals, respectively, with pairs of values of ε_L and ε_N and t statistics of ⟨0.113 (3.66), 0.061 (1.85)⟩; ⟨0.086 (3.61), −0.072 (2.51)⟩; ⟨ 0.096 (4.59), 0.089 (4.05)⟩; and ⟨ 0.027 (1.22), 0.007 (.29)⟩.

2.3. Other Sources of Scale Effects

There remains a question not asked previously of whether scale economies for an industry rather than resulting from only either own industry scale or general urban scale might come from the scale of related industries. To determine which are related industries, one could use cluster analysis to determine which industries tend to locate together and then see if productivity in an industry is affected by the scale of related industries (other industries in the cluster). However, it is critical to note that similar location patterns may in no way be connected with scale effects, but may simply be connected with, for example, transport cost considerations. For example, steel production generally occurs only where there are limestone deposits. However, the scale of employment in local limestone extraction and processing may not enhance *productivity* in steel production, even if close proximity enhances profitability.

A drawback of this procedure is that, when estimating productivity equations, measures of own scale of related industries are by definition highly collinear, given the basis for selecting the latter. Thus, in any estimation, one must have serious doubts about whether the effects of scale of related industries have been separated out from the fact of close proximity per se.

For the U.S., using cluster analysis on 229 industries, we tried this procedure. The results were discouraging in that no patterns emerged in any experimentations, and they certainly did not place the results on localization and urbanization economies under suspicion. For example, for the base two-digit industries, related input industries actually registered negative productivity effects in six cases, and only positive impacts in five cases. Four industries had no related input industries (and most had no related output industries).

2.4. Nonexternal-Economy Variables

The estimating equations contain variables relating to input prices, capital-to-labor ratios (Brazil), labor force quality, and firm size. Due to space limitations, the results are not reported here, but are available on request from the author. We have a few comments on the results. In (5a), the wage terms are generally positive and significant, indicating expected negative own gross substitution effects. In (2), the capital-to-labor ratio is generally significant with expected magnitudes.

Great attention was paid to labor force quality measures with disappointing results. While productivity seems weakly related to age, controlling for educational attainment seems irrelevant to productivity. In Brazil the percentage of the labor force with three or less years of schooling (effective illiteracy) produced an "incorrect" sign 50% of the time. Experimenting with different threshold attainment levels produced equally dismal results. This result contrasts with results obtained from estimating wage equations (e.g., Brown and Medoff [1978], as well as our own experiments). There is an obvious implication that while wage setting policies incorporate education, productivity in manufacturing may not respond. Since this is the first reported work we know of to directly test for the impact of education per se *industry-by-industry* (Brown and Medoff construct a "quality index" combining sex, age, schooling, and regional variables), it suggests that more work is needed on this subject.

In terms of other variables, inclusion of firm size allows us to test the assumption that firm production functions are homogeneous of degree one. For both Brazil and the United States, average firm size had no consistent impact on productivity across industries and often no robust effect across specifications within an industry. Moreover, in Brazil, any positive firm size effects seemed to reflect industry composition differences (e.g., for furniture) across cities between factory standardized products and small-scale special-order products (which are quite different products to the consumer).

2.5. Hicks' Neutrality

The discussion of external economies presumes Hicks' neutrality. Here, we can directly test that assumption for Brazil. Taking marginal productivity conditions for capital and labor based on Eq. (2) and combining, we get the general result

$$k = k(p_L, p_K, \mathbf{S}) \tag{7}$$

where k is the capital-to-labor ratio, p_L and p_K the factor prices of labor and capital, and $\mathbf{S}$ the vector of scale and technology measures. If the impact of these later measures on production is Hicks' neutral, then the impact of $\mathbf{S}$ on k should be zero. A significant positive or negative impact would indicate that scale or technology improvements are, respectively, capital or labor using. Thus, estimating (7) constitutes a direct test of Hicks' neutrality. In estimating we assume the pretax cost of capital is either the same everywhere or increases with distance from major financial centers. The posttax cost of capital varies with the effective local property tax rate on capital, specific to industry and urban area. Based on variable definitions in Appendix C, the estimating equation is

$$\begin{aligned} \ln(k) = \alpha_0 + \beta_1 \log(p_L) + \beta_2 u + \beta_3 pt + \beta_4 \text{ percent illiterate} \\ + \beta_5 \text{ average age } + \beta_6 \ln(fs) + \beta_7 \ln(L). \end{aligned} \tag{7a}$$

The results for the industries represented in Table 1 are in Table 3.

TABLE 3

Determinants of K/L Ratio for Brazil: Major Industries and Subindustries

	$\ln(p_L)$	Prop. tax	u	% < 3 yrs ed.	Avg. age	$\ln(fs)$	Scale ($\ln(L)$)	Const.	Adj. R^2	N
Textiles	.827	4.611	.002	1.326	-.045	.069	.051	1.887	.24	58
	(2.62)	(2.19)	(1.71)	(1.74)	(.89)	(.80)	(.81)	(.80)		
Iron and steel	1.293	1.219	.074	.985	.019	.305	.025	1.264	.40	36
	(2.57)	(11.61)	(1.09)	(.73)	(.22)	(1.72)	(.21)			
Chemicals	.717	3.684	.132	n.a.	n.a.	.021	.209	.497	.42	29
	(1.83)	(1.23)	(1.79)			(.14)	(1.60)			
Transport equip.	.443	18.699	.020	n.a.	n.a.	.089	.005	1.969	.57	27
	(1.00)	(3.75)	(.30)			(.53)	(.04)			
Nonelect. machinery	.182	7.953	.086	.561	.025	.138	.017	3.710	.40	57
	(.75)	(4.85)	(2.41)	(1.07)	(1.22)	(1.87)	(.29)			
Nonmetallic minerals	.474	8.133	.035	.251	.025	.153	.073	.220	.43	83
	(3.44)	(4.41)	(1.17)	(.62)	(1.09)	(1.25)	(1.07)			
Apparel	.792	2.558	.050	.011	.0004	.101	.093	1.666	.24	42
	(2.59)	(2.15)	(1.59)	(.01)	(.03)	(.95)	(1.83)			
Pulp and paper	.377	19.871	.102	n.a.	n.a.	.097	.090	-1.002	.501	21
	(.71)	(1.41)	(.81)			(3.48)	(.55)			
Food processing	.745	-2.594	.074	.181	.022	.093	.054	2.244	.18	108
	(3.82)	(2.43)	(2.76)	(.36)	(1.00)	(.74)	(.83)			
Furniture	.316	9.842	.020	.561	.029	.209	.036	2.655	.22	53
	(1.19)	(4.33)	(.68)	(.83)	(1.11)	(1.34)	(.50)			
Printing	.287	6.846	-.041			.083	-.011	1.872	.38	32
	(1.05)	(3.27)	(1.53)	n.a.	n.a.	(.43)	(.16)			

In terms of scale effects, across industries the sign patterns are completely mixed and the variable is never significant at the 5% level. We reject the hypothesis of nonneutrality of scale effects and conclude that external economies are Hicks' neutral in their impacts on capital and labor. Addition of an urbanization economy measure (log N) produces the same neutrality conclusion.

We also note that (7a) is well behaved. For example, the price variables (p_L and pt) have expected signs and consistent magnitudes, where either raising p_L or lowering the cost of capital by 1% should have the same percentage impact on k (so as to imply the same elasticity of substitution).[17]

3. CONCLUSIONS

In general, external economies of scale are ones of localization, not urbanization. Localization economies are strongest for industries in which

[17] A 1% increase in p_L typically raises k by 0.8%. A 1% increase in the cost of capital (interest and depreciation of 0.13 plus a typical property tax rate of 0.02) leads to typically a 1% decrease in k (for a coefficient of pt of -7, the elasticity is $-7*0.15$).

cities tend to specialize and peter out as city size increases. The implication is that resources in manufacturing are generally not more productive in larger cities—they may even be less productive. Rather, resources in any industry are more productive in places where there is more of similar activities. However, the fact that scale effects die out means that there is a limit to the benefits of agglomerating similar activity. Based on these facts, we expect to find that small and medium size cities are highly specialized in production.

APPENDIX A: CORE CLUSTERS OF SMSA'S FOR THE U.S.

To do the cluster analysis, a 229 industry × 243 SMSA matrix of the fractions of an SMSA's employment in each of 229 industries (from Table 1270 of the Sixth Count of the 1970 Population Census) for 243 SMSA's was formed. From that matrix a 243 × 243 symmetric matrix of simple correlation coefficients between pairs of columns of employment fractions for each pair of SMSA's was formed. The correlation coefficients measure the degree of similarity or dissimilarity (for negative coefficients) between employment patterns of each pair of SMSA's. The primitive cluster algorithm picks the highest correlation coefficient and combines those two SMSA's, reducing the rows and columns of the matrix by one. In terms of the correlation between the combined SMSA's and any remaining SMSA, the algorithm picks either the highest or lowest of the pair of coefficients between that remaining SMSA and the original SMSA's which were "combined." The results in Table A1 are based on retaining the lowest. For the new 242 × 242 matrix the algorithm then repeats itself, picking the highest correlation coefficient and combining two SMSA's to be the start of a (probably) new cluster. The results in Table 1 are based on the clustering stopping at a correlation of .48. Most clusters have a minimum correlation coefficient for the last SMSA added of .6.

APPENDIX B: U.S. DATA INFORMATION

Primary data sources are the 1972 Census of Manufacturers and the 1970 Census of Population. In moving between 1970 and 1972 we accounted for the grouping of eight 1970 SMSA's into four 1972 SMSA's, and the 1970 urban population measure is based on 1972 SMSA definitions. Key variable definitions are in Table B1. Instruments used in Table 2 estimations are driving time to regional market, regional dummies, annual precipitation, % heating degree days, coastal dummy, labor force participation females, % males commuting to CBD, % families with children, % public administrative employees over 60, % population with college degree, % of manufacturing employees who are black, ratio of state to federal employees, % state labor force unionized, farm population of state, % housing built before 1950,

TABLE A1

Auto
- Bay City, MI (13%)
- Cleveland, OH
- Detroit, MI (17%)
- Flint, MI (36%)
- Jackson, MI (7%)
- Kenoska, WI (16%)
- Lansing, MI (15%)
- Muncie, TN (13%)
- Saginaw, MI (17%)
- South Bend, IN (6%)
- Springfield, OH (9%)
- Toledo (OH–MI) (8%)

Textiles (excluding apparel)
- Ashville, NC (7%*)
- Augusta, GA (10%)
- Chattanooga, TE–GA (11%)
- Columbus, GA (11%*)
- Greenville, SC (18%)
- Wilmington, NC (7%)

Food processing (excluding agriculture, fisheries, and wholesaling)
- Brownsville–Harlington–San Benito, TX (4%*)
- McAllen–Phan–Edinburg, TX (2%*)
- Modesto, CA (9%*)
- Salinas–Monterey, CA (4%*)
- Stockton, Ca (5%)

Aircraft
- Anaheim–Santa Ana–Garden Grove, CA (5%)
- Bridgeport, CT (7%)
- Fort Worth, TX (13%)
- Hartford, CT (11%)
- Seattle–Everett, WA (10%)
- Wichita, KA (14%)

Radio, television and communication equip.
- Binghamton, NY–PA (7%)
- Cedar Rapids, IA
- Lawrence–Haverhill, MA–NH (7%)
- Nashua, NY (8%)

Pulp and paper
- Appleton–Oshkosh, WI (13%)
- Green Bay, WI (11%)
- Mobile, AL (6%*)
- Monroe, LA (6%*)
- Portland, ME (4%*)
- Savannah, GA (5%*)

Shipbuilding
- Charleston, SC (7%)
- New London–Groton–Norwich, CT (12%)
- Newport–New Hampton, VA (17%)
- Vallejo–Napa, CA (10%)

Apparel
- Allentown–Bethlehem–Easton, PA–NJ (9%)
- Atlantic City, NJ (5%*)
- El Paso, TX (8%*)
- Fall River, MA–RI (16%)
- New Bedford, MA (13%)
- Scranton, PA (11%*)
- Wilkes–Barre–Hazelton, PA (12%*)

College state capital towns
- Austin, TX
- Bloomington–Normal, IL
- Bryant–College Station, TX
- Champaign–Urbana, IL
- Columbia, MO
- Columbus, OH
- Durham, NC
- Fargo–Moorhead, ND–MN
- Gainesville, FL
- Lafayette, LA
- Lafayette–W. Lafayette, IN
- Lexington, KY
- Lincoln, NE
- Lubbock, TX
- Madison, WI
- Raleigh, NC
- Reno, NV
- Santa Barbara, CA
- Tallahassee, FL
- Terre Haute, IN
- Tucson, AZ
- Tuscaloosa, AL

Steel
- Birmingham, AL (8%)
- Gasden, AL (11%)
- Gary Hammond–East Chicago, IN (26%)
- Huntington–Ashland (WV, KY, OH) (7%)
- Johntown, PA (13%)
- Pittsburgh, PA (9%*)
- Pueblo, CO (8%)
- Steubenville–Weirton, OH–WV (29%)
- Wheeling (WV–OH) (7%)

Leather products
- Brockton, MA (6%)
- Lewiston–Auburn, ME (16%*)
- Manchester, NH (7%*)

Petrochemicals
- Baton Rouge, LA (10%*)
- Beaumont–Port Arthur–Orange, TX (18%*)
- Galveston–Texas City, TX (11%*)
- Lake Charles, LA (12%*)

Service centers
- Amarillo, TX
- Billings, MT
- Duluth–Superior, MN
- Little Rock–North Little Rock, AR
- Omaha, NE
- Spokane, WA
- Springfield, MA

Diverse manufacturing
- Chicago, IL
- Dallas, TX
- Newark, NJ
- Philadelphia, PA
- Phoenix, AZ
- Syracuse, NY

Industrial machinery
- Bristol, CT (10%)
- Canton, OH (6%)
- LaCrosse, WI (11%)
- New Britain, CT (10%)

Note. An asterisk (*) indicates that the employment fractions in parentheses are a *lower* bound number, not the actual number.

TABLE B1

Variable Definitions and Sources

Variable	Definition
Y	Value of production from Manufacturing Census
L	Annual hours of work for production workers plus 2000 hours/year times number of nonproduction workers
p_L	Total wages and salaries divided by L
% < 8 years of schooling	Percentage of two-digit industry specific labor with 8 or less years of schooling as calculated from Sixth Count of 1970 Population Census by combining Table 124D of education by 27 manufacturing occupations in each SMSA with Table 1250 of 27 occupations by 20 manufacturing industries to get SMSA specific matrices of education by industry
% > 55 years of age	Percentage of the two-digit specific labor force which is 55 years of age or older from Table 1290 of Sixth Count of 1970 Population Census
u	Distance to the nearest regional market center. These are the 27 National Business Centers, as defined by Rand McNally (based on the volume of financial activity and wholesale and retail trade). Distance is in hours of driving time based on Rand McNally estimates (with gaps filled in based upon likely routes and speeds of travel). We also calculated driving times to the nearest of six national market centers (New York, Chicago, Los Angeles, San Francisco, Atlanta, and Dallas).

multiple name SMSA, % females in manufacturing, driving time to national market, federal and state % of total SMSA revenue, % of families housed in one-unit structures, and cost of electrical power. These are taken from *1972 City and County Data Book*, *Climatological Data* (National Oceanic and Atmospheric Administration) 1976, *1972 Statistical Abstract*, *Waterborne Commerce of the U.S.A.* (U.S. Corps of Engineers) *1972 Census of Governments*, *Uniform Crime Report*, 1970 and 1971 (FBI), *Typical Electric Bills* (U.S. Federal Power Commission) 1970, and 1970 Population Census.

APPENDIX C: VARIABLE DEFINITIONS FOR BRAZIL

Variable	Definition
Y	Value-added: value of production less total materials costs less production taxes. Production tax rates vary spatially and their differences may not be passed onto consumers. Including production taxes in value added has minimal impact on the results.
L	Average monthly number of employees less owners and directors (a trivial number). Hours of work information is not collected.
P_L	Total salaries less payments to owners and directors *plus* firm contributions to Social Security, private insurance, and pension programs, all divided by L.
k	Market value of capital stock.[a] Census question asks what firms could sell their equipment, structures, and land for today (other questions ask book value and depreciated book value).
fs	Average firm size: L divided by number of firms.
pt	Property tax rate: industry property tax payments divided by K. This varies by industry and urban area according to exemptions granted.
% Illiterate	Percentage of labor force by two-digit industries with three or less years of schooling. Calculated directly from 25% "long-form" sample of 1970 Demographic Census.
Age	Average age of labor force by two-digit industry (from 1970 Demographic Census).
u	Distance in kilometers to nearest coastal port. For all six ports the urban area is a major metropolitan area. There is only one major interior metropolitan area in the sample, Belo Horizonte. São Paulo is counted as a "port" although it is 75 km from the sea and the actual port is Santos.

[a] Is this a good measure of physical units? If capital is perfectly malleable, since a depreciated *quantity* of capital has the same *value* as the same quantity of new capital (where value equals cost of producing new units of capital in perfect competition), the quantity of capital is directly proportional to the value of capital irregardless of age distribution. Value is also approximately proportional to quantity irregardless of age distribution if capital is nonmalleable but "infinitely" lived and decaying expotentially.

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Household Formation and Suburbanization, 1970–1980*

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1. INTRODUCTION

Metropolitan populations in the U.S. have been deconcentrating throughout the last hundred years. Urban observers have recently noticed that central city numbers of some population subgroups have increased, and have suggested that this "back-to-the-city" movement may bring an end to a century of deconcentration. Whether this city repopulation is the start of a long-term trend or only a temporary phase is the subject of this paper.

Metropolitan deconcentration has been thoroughly documented up to 1960 by Mills [7], who attributes the phenomenon to real income and population growth. Macauley [6] has recently updated Mills' study to 1980, and concludes that deconcentration may be slowing but is not stopping. The slowdown is attributed to sluggish income and population growth during the seventies, an explanation consistent with the other major slowdown in urban deconcentration, during the Great Depression.[1]

Against this background of continuing suburbanization has come the back to the city movement, which can be dated in some cities to the fifties but is generally thought to have begun in the early to midseventies.[2] The people involved in ths movement tended to be young relatively affluent childless couples, who frequently bought a rundown property near the city core to renovate. Alonso [1] traces the origins of the movement to the baby boom, which produced a very large cohort entering the traditional

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[1]Estimates from the two studies show that the average rate at which the logarithm of population density declines per mile from the city center is decreasing, as argued, but unevenly through time. Between 1920 and 1929, the average rate dropped 1.45% per year, but between 1930 and 1939 it dropped only 0.82% yearly. In the years 1940 to 1948 the rate of decline accelerated to 1.66%. The big change came in 1949 to 1958, when the rate jumped to 2.8%. The rate slowed somewhat in the 1959–1969 period to 2.64%, and dropped considerably in the 1970–1980 period to 1.79%.

[2]See [5] for references and case studies.

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