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This paper uses data for eight manufacturing industries in 1970 and 1987 to test for and characterize dynamic production externalities in cities. We find evidence of both MAR externalities, which are associated with past own industry employment concentration, and Jacobs externalities, which are associated with past diversity of local total employment. More specifically, for mature capital goods industries, there is evidence of MAR externalities but none of Jacobs externalities. For new high-tech industries, there is evidence of Jacobs and MAR externalities. These findings are consistent with notions of urban specialization and product cycles: new industries prosper in large, diverse metropolitan areas, but with maturity, production decentralizes to smaller, more specialized cities. For mature industries, there is also a high degree of persistence in individual employment patterns across cities, fostered by both MAR externalities and persistence in regional comparative advantage.

The literature on endogenous growth models argues that dynamic information externalities are the driving force for technological inno-

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vation and hence economic growth (Romer 1986). Since these externalities arise from both intended and unintended communications among economic agents over time, their effects should be more readily observed in places in which communications are focused. As noted by Lucas (1988), this intuition suggests that cities provide a natural laboratory to study the nature and extent of these externalities. This paper is an empirical investigation of the nature of dynamic externalities and their implications for urban development, for a selection of both mature and new high-tech industries.

The study of externalities in urban environments has a long history (e.g., Hoover 1937; Chinitz 1961), but empirical work has focused on static externalities, such as immediate information spillovers about current market conditions. There are two types of static externalities: localization economies in which a firm benefits from local firms in just the same industry, and urbanization economies in which a firm benefits from overall local urban scale and diversity. Both types suggest benefits of being in bigger cities, but as we know, city sizes are limited by overall local congestion and commuting costs (Mills 1967). Given this, with localization economies, cities will tend to specialize to enhance own industry agglomeration benefits relative to commuting and congestion costs. Their sizes will depend on their products and the associated degree of localization economies (Henderson 1974). On the other hand, if urbanization economies dominate for an industry, firms will seek more diversified larger cities. Thus in a snapshot of cities, we see smaller and medium-size textile, apparel, transport equipment, primary metals, food processing, pulp and paper, and so forth type cities in which localization economies dominate; but industries such as high-fashion apparel, upper-end publishing, and many business services subject to urbanization economies agglomerate in very large metropolitan areas (Henderson 1988).

Dynamic externalities deal with the role of prior information accumulations in the local area on current productivity and hence employment. Such accumulations are fostered by a history of interactions and cultivated long-term relationships, which lead to a buildup of knowledge ("local trade secrets"), available to firms just in a local area. As in their static counterparts, there are two types of dynamic externalities. With terminology used in Glaeser et al. (1992), dynamic externalities may be Marshall-Arrow-Romer (MAR) (localization) economies, which derive from a buildup of knowledge associated with ongoing communications among local firms in the same industry, or Jacobs (1969) (urbanization) economies, which derive from a buildup of knowledge or ideas associated with historical diversity. As shown in a snapshot of cities, dynamic externalities can have implications similar to those of static externalities. For example, in the steady state, an industry with a higher degree of MAR externalities is likely to locate in a larger specialized city type than an industry with lower MAR externalities. However, dynamic externalities have broader implications concerning industrial development over time. They help provide an explanation for the location and growth patterns of both mature and newer industries, which we observe in a series of snapshots of an economy.

For mature industries we observe a very high degree of persistence in employment patterns across cities over time. There is very slow mean reversion, or "convergence" in the raw data on individual industry employments. This persistence occurs despite both high plant and employment turnover rates for individual manufacturing industries (see, respectively, Dunne, Roberts, and Samuelson 1989*a*, 1989*b*; Davis and Haltiwanger 1991) and despite strong evidence that plants relocate as local wages and demand conditions change (see Herzog and Schlottmann 1991). If employment concentrations across cities were determined solely by a random draw of just current economic conditions, we would expect strong reversion to the mean over time in individual industry employment levels across cities. We shall show that part of the glue that holds employment concentrations of an industry in specific cities over time is MAR externalities. Cities with historical concentrations of an industry and related local knowledge accumulations will offer a more productive environment for establishments in that industry than those without them. They will be able to better compete for and, over time, retain plants and employment in that industry.

For newer high-tech industries, persistence is not so relevant, since industrial location patterns are new. Instead we observe growth in the number of cities having an industry and in employment levels within those cities. The natural question concerns what historical environments have an advantage in the ongoing race to attract newer industries, recognizing that for any new industry only a few cities will ultimately be winners. Part of the answer will lie with dynamic externalities. In particular, we shall show that new high-tech industries are more likely to take root in cities with a history of industrial diversity, suggesting that Jacobs externalities are important for these industries. Taken together, our results for mature and new industries are consistent with urban product cycle notions. New products are developed in large diverse metro areas with a diversified skill base, but matured product lines subject to MAR effects eventually decentralize to smaller, more specialized metro areas, with lower wage and land costs.

In previous studies of dynamic externalities, Jaffe, Trajtenberg, and Henderson (1993), in studying patent citations, find that such externalities are localized and diffuse slowly over space. In studying employment growth for 170 standard metropolitan statistical areas

(SMSAs) between 1956 and 1987 for the six largest industries in each city in 1956, Glaeser et al. (1992) conclude that, for all economic activity lumped together, dynamic externalities are only Jacobs in nature. For total manufacturing, Miracky (1992) finds some evidence of both MAR and Jacobs externalities for the period 1977–87.

Our data describe employment growth patterns in eight specific manufacturing industries in 224 metropolitan areas between 1970 and 1987. We examine the five key traditional capital goods industries that cities tend to specialize in and whose products are widely traded across cities: primary metals, machinery, electrical machinery, transport equipment, and instruments. We also examine three "new" high-tech industries—computers, electronic components, and medical equipment—to study key aspects of their recent development in cities.

Our methodology and basic results differ from those of previous studies. As already implied, we find intuitively appealing results—only MAR externalities for mature industries and both MAR and Jacobs externalities for new high-tech industries—that are consistent with notions of persistence and urban product cycles. Relative to previous work, we find that it is critical (1) to distinguish between industries and to include newer industries in the sample since externalities vary by industry and stage of product development, (2) to include for each industry the entire available sample of cities, and (3) to incorporate other traditional considerations besides externalities that affect local industry growth, such as local labor market and regional product demand conditions.

In Section I of the paper, we present and estimate the model for five traditional heavy-manufacturing industries, to explore the nature of dynamic externalities for those industries. In Section II, we turn to the three newer high-tech industries. Section III presents conclusions.

I. Traditional Industries

This section examines 1987 employment patterns in five two-digit manufacturing industries: machinery, electrical machinery, primary metals, transportation, and instruments. Information on these industries for 1970 and 1987 is presented in table B1 in Appendix B. On the basis of uncensored 1970 data, it appears that these industries are found in all cities. Except for instruments, these industries have stagnated or declined nationally since 1970.

To test for dynamic externalities, we model 1987 city employment in each industry as a function of historical (1970) and current conditions in cities. For an industry in location i at time t, the equilibrium employment level is such that the local wage rate equals the value of marginal product (VMP), or $W_{it} = A_{it}(\cdot)f'(N_{it}; \ldots)P_{it}(\cdot)$. Industry output is $A_{it}(\cdot)f(N_{it}; \ldots)$, and N_{it} is employment in the industry in location i in time t. The term $A_{it}(\cdot)$ represents the state of technology for that industry in location i in time t; W_{it} is the nominal wage rate, which varies enormously across localities for workers with similar skills; and P_{it} is the price of output, given by the inverse demand function $P_{it}(\cdot) = P(N_{it}, MC_{it})$. From the literature,[1] we know that for a city, $P_{it}(\cdot)$ is downward sloping in local industry output (represented by N_{it}); and its other arguments, MC_{it}, include regional characteristics, access to major urban market centers, and local metro area demand for capital good products.

For the arguments of $A_{it}(\cdot)$, the traditional production externality literature focuses on static externalities that arise from current local own industry scale, or employment, N_{it}. Dynamic externalities deal with aspects of the historical urban environment: in particular, own industry employment in some base period, N_{i0}, concentration of that employment, ρ_{i0}, and diversity of the environment, D_{i0}. Cicone and Hall (1993) as well as Glaeser et al. (1992) argue that concentration, ρ_{i0} (vs. levels, N_{i0}), may better represent the potential for MAR externalities since concentration facilitates spillover or "network" information flows among relevant firms and the development of location-specific knowledge, relative to a location with diffuse economic activity. A diversity measure represents the potential for Jacobs externalities, where, for example, product development may prosper in an environment in which there is a history and tradition of economic and social interaction among diverse economic sectors. Combining static and dynamic externalities, in summary, for A_{it} we have $A_{it} = A(N_{it}, N_{i0}, \rho_{i0}, D_{i0}, \ldots)$. Substituting the expressions for $P_{it}(\cdot)$ and $A_{it}(\cdot)$ into the VMP equals the wage equation, and inverting, we get a reduced-form equation

$$N_{it} = N(W_{it}, MC_{it}, N_{i0}, \rho_{i0}, D_{i0}, \ldots). \tag{1}$$

Note that this equation can also be transformed into a growth rate equation, where $\log(N_{it}/N_{i0}) = \tilde{N}(\cdot)$. In equation (1), since $\partial[A(\cdot)f'(\cdot)P(\cdot)]/\partial N_{it} < 0$ for equilibrium in labor markets, a well-behaved equilibrium requires $\operatorname{sign}[\partial N_{it}/\partial N_{i0}] = \operatorname{sign}[\partial A_{it}(\cdot)/\partial N_{i0}]$. This comment applies to any historical argument of $A_{it}(\cdot)$. For example, if MAR effects matter, then an increase in ρ_{i0} increases worker productivity and thus increases local industry employment for a given wage.

[1] See Herzog and Schlottman (1991). As a specific example, for machinery and electrical machinery, Henderson (1993) finds that, on average, sales to Mexico decline by, respectively, 2.6 percent and 1.1 percent for each 55-mile distance increment of a U.S. plant site from the Mexican border.

Glaeser et al. (1992) arrive at a formulation such as (1) by forming the ratio for wage equals VMP equations in years t and 0 and asserting that the growth in $A(\cdot)$, $\log(A_{it}/A_{i0})$, is a function only of ρ_{i0}, D_{i0}, and N_{i0}. The resulting reduced-form equation corresponds to equation (1), except W_{i0} and MC_{i0} are added. Our results on dynamic externalities in equation (1) with and without the W_{i0} and MC_{i0} arguments are almost identical.

A. *Data and Estimation*

The data pertain to 1970 and 1987, and sources and definitions are discussed in Appendix A. We focus on the 224 SMSAs in 1970 that can be matched to 1987 Metropolitan Statistical Areas (MSAs) or Primary Metropolitan Statistical Areas (PMSAs). These proposed estimations raise a variety of econometric issues. First, equation (1) may contain fixed effects that are correlated with historical variables. Second, our sample of 224 cities from 1970 excludes 81 new cities since 1970, which raises selectivity issues. Later we note efforts to test and account for these problems.

A critical issue for any implementation of equation (1) is that our 1987 *Census of Manufactures* data on employment levels are censored. A city reports zero employment for an industry if employment is less than 250 in that industry in that city in 1987. We therefore use a Tobit formulation in estimation of (1), presuming that all our industries have in fact some minimal employment in any city (see the 1970 numbers in table B1), but about 30 percent of MSAs for the typical industry in 1987 are censored (table B1).

In the rest of this section, we present our basic results on equation (1) for the five two-digit capital goods industries. The presentation is divided into two parts. First we focus on the results concerning dynamic externalities and the effect of history, controlling for current wages, W_{it}, and market conditions, MC_{it}. The estimated coefficients for W_{it} and MC_{it} in equation (1) are presented in table B3 and are briefly discussed in subsection *C*. In that subsection we also deal with other estimation issues.

B. *Basic Results*

In table 1 we present results for equation (1) pertaining just to the effect of history on current employment. These results measure the nature and extent of dynamic externalities. In table 1, history is described by three measures: two relating to own industry employment in 1970 and one relating to industrial diversity of the city in 1970. As discussed earlier, for own industry activity, concentration is thought to represent MAR externalities more directly since it facili-

TABLE 1

DETERMINANTS OF LOG(1987 OWN INDUSTRY EMPLOYMENT): HISTORICAL CONDITIONS

	Machinery	Electrical Machinery	Primary Metals	Transportation	Instruments
Log(1970 own industry employment)	.547*	.592*	.647*	.532*	.365*
	(.070)	(.075)	(.065)	(.102)	(.087)
Concentration 1970: ratio of own industry employment	8.416*	6.672*	4.002**	9.879*	14.926*
to total civilian employment	(2.213)	(2.615)	(2.161)	(3.911)	(7.112)
Index 1970: lack of diversity	.246	−.578	−.250	−.564	−1.904
	(.548)	(.881)	(1.05)	(1.207)	(1.275)

NOTE.—Standard errors are in parentheses.
* Significant at the 5 percent level.
** Significant at the 10 percent level.

tates spillover or "network" information flows among relevant firms. The own industry level measure represents remaining persistence in employment levels.

In table 1, for the own industry level measure, the coefficients on log(1970 own industry employment) are about .5. To get a perspective on these coefficients, it is helpful to interpret them in a Barro and Sala-i-Martin (1991) growth framework, where $\ln(N_{87}/N_{70}) = \alpha - \delta \ln N_{70}$. In that context, a coefficient of .5 in equation (1) states that $1 - \delta = .5$. The implied δ of .5 suggests an annual rate of convergence, β, of about 4 percent a year ($\delta = 1 - \exp[\beta T]$ for $T = 17$ years). This is relatively quick "mean reversion." This quick reversion occurs only in estimation of equation (1) because we have controlled for other historical and current market conditions in tables 1 and B3. Table B2 shows that if we do not control for these conditions, there is much greater overall persistence in individual industry employment patterns. Convergence rates in the basic data are about 1 percent for individual industries and are near zero for manufacturing as a whole. We shall comment on this further below.

The degree of past concentration, the basic MAR measure, strongly affects current employment. Past concentration in table 1 is measured by the ratio of own industry employment to total local civilian employment in 1970. The coefficients for this variable are positive, large, and significant, indicating that historical concentration of the own industry creates an environment conducive to attracting current producers. Consider machinery. When 1970 machinery employment is held fixed, a one-standard-deviation (.030) increase in the share of machinery in overall local employment in 1970 increases 1987 machinery employment by 25 percent. If we compare a city with 20,000 workers in 1970 who constitute 2 percent of the workforce with a city with 10,000 machinery workers who constitute 8 percent of the workforce in 1970, the second city would have a larger workforce in machinery in 1987, ceteris paribus. For our five industries, table 2 calculates the percentage change in 1987 employment of a one-standard-deviation (see App. A) increase in the degree of own industry concentration in 1970. The MAR effects are largest for transport equipment and machinery. Both tend to be found in larger types of specialized cities (Henderson 1988).

As an alternative measure of concentration, we used the ratio of own industry employment to total local effective urban land area using land area data from a 1972 Department of Transportation study of urban land use, intracity highways, and roads (*1974 Transportation Report*). This measure attempts to capture the spatial (density) connotation of MAR externalities. This variable is always positive in

TABLE 2

MAR EFFECTS: PERCENTAGE IMPACT ON CURRENT EMPLOYMENT OF A ONE-STANDARD-DEVIATION INCREASE IN 1970 OWN INDUSTRY CONCENTRATION

Machinery	Electrical Machinery	Primary Metals	Transportation Equipment	Instruments
25%	22%	16%	31%	19%

sign and has reasonable statistical significance;[2] but including it with the employment concentration measure adds no explanatory power, with the employment measure dominating. As another alternative, from a technical point of view, including both a level and an employment concentration measure in equation (1) would be similar to just having level measures for 1970 own industry employment and for 1970 total civilian employment.[3] Doing so produces the expected negative (and generally significant) coefficient for 1970 total civilian employment.

Besides own industry employment and concentration, historical diversity of the urban industrial base might positively affect current employment in an industry, suggesting the presence of Jacobs-type dynamic externalities. Accordingly, we constructed separate diversity measures for all other historical economic activity, all other manufacturing activity, and relevant wholesale, business, and professional service activities. In table 1, we report the results for one of these measures: diversity of all other manufacturing in 1970 based on a Hirschman-Herfindahl index for about 50 three-digit manufacturing industries. The Hirschman-Herfindahl index for city i for two-digit industry k, HHI_{ik}, is

$$\mathrm{HHI}_{ik} = \sum_{j \notin k} s_{ij}^2, \qquad (2)$$

[2] The coefficients and standard errors for our five industries in table 1 are, respectively, .0034 (.0020), .0100 (.0031), .0093 (.0041), .0015 (.0017), and .0030 (.0036) for a typical mean and standard deviation of the variable of 19.7 and 28.2 (for electrical machinery).

[3] Our results on past concentration and MAR effects differ from those in Glaeser et al. We consistently get a positive impact using either our specification of the estimating equation or theirs (i.e., whether we control for current or 1970 economic conditions or both). They get a negative impact. However, the samples (and time periods) differ. Glaeser et al. include an industry only if it is one of the six largest industries in a city. So, by definition in their sample, all industries have high degrees of concentration in 1956, whereas we cover the whole spectrum. Second, nontraded sectors such as wholesaling, retailing, and traditional services are heavily represented in their sample, with manufacturing industries accounting for about one-third of their observations. In a recent paper, Miracky (1992) finds that past concentration has a significant impact in manufacturing, but not for all industries lumped together.

where s_{ij} is the share in city i of three-digit manufacturing industry j in local all other manufacturing employment. An increase in HHI_{ik} reflects less diversity in the environment. If employment in 50 other three-digit industries is evenly distributed, the index has a value of .02; if it is concentrated all in one other three-digit industry, it has a value of one. As is apparent in table 1, diversity of all other manufacturing activity has no consistent or significant impact on 1987 employment. Further, as detailed in Henderson, Kuncoro, and Turner (1992), we experimented extensively with the other measures of historical diversity noted above, as well as specific historical levels and shares of interconnected activities for each industry based on input-output tables and locational associations. *None* of these measures had a consistent or significant impact on 1987 employment, whether entered separately, in pairs, all together, and so forth. Indications of Jacobs effects of any kind are absent. The strongest possibility in table 1 is for instruments, our only growing industry. This could suggest that Jacobs externalities might occur for rapidly developing industries, a notion we explore in Section II.

C. *Other Results and Issues*

1. Output and Labor Market Controls in Equation (1)

Table B3 presents results on output and labor market conditions. Output market conditions are represented by regional dummies, an access measure, and a measure of local demand for the industry. Regional dummies represent the effect of regional demand conditions, with 1970 employment controlled for (in table 1). Typically, from 1970, relative to the West (the constant term) and South, industries have declined in the Northeast and Midwest, as manufacturing has shifted with regional population and demand shifts. Access is distance from an MSA to the nearest of the 30 Rand McNally national business centers. Distance to markets matters, repressing the demand for a locality's output. Finally, we measure local demand for the products of our capital goods industries by employment in all other manufacturing. Major portions of the output of our industries are inputs for other manufacturing industries. For current all other manufacturing employment, a 1 percent increase in employment increases own industry employment by 0.3–1.0 percent. A static externality interpretation for this variable is also possible since other manufacturing could enhance productivity in any one industry by enhancing static information flows.

The second block of variables in table B3 represents current labor market conditions.[4] Higher current wages generally reduce demand substantially. A 1 percent rise in wages reduces employment by about 1 percent on average. Correspondingly, improvements in labor force quality as measured by increases in educational attainment of the adult population generally increase the demand by an industry to locate in a city. This variable can also have a static externality interpretation, where a more educated local population enhances an industry's productivity. Finally, we experimented with other measures of current economic conditions, such as state fuel and electrical prices, diversity of the local industrial environment (see eq. [2] above), median residential rents, coastal location, and contiguity of PMSAs in a consolidated metropolitan area. All were insignificant and inconsistent in their own impact and had no consistent or strong impacts on reported variables in tables 1 and B3.

2. Persistence

What variables are responsible for the drop in the coefficient of log(1970 own industry employment) from around .8 to .9 for the basic data in table B2 to around .5 in table 1? Experimentation revealed that log(1987 all other manufacturing employment) in equation (1) (see table B3) is responsible for much of the drop in log(1970 own industry employment), with the historical concentration measure responsible for the rest. Omitting log(1987 all other manufacturing), a key derived-demand variable, would lead to an overstatement of inherent persistence of own industry employment.[5] In table B2, there is a very high degree of persistence in overall other manufacturing employment in cities. Our estimates in table 1 suggest that this persistence translates into a persistent derived-demand base for individual industries, explaining a lot of the persistence in the raw data for these individual industries.

Why is all other manufacturing persistent? Some preliminary work suggests that regional comparative advantage forms part of the explanation. First, the 1987 ratio of local total manufacturing to total civil-

[4] Data availability at the time of sample construction required us to use 1982 manufacturing wages and 1980 educational measures as current labor market conditions.

[5] There could be an issue of whether inclusion of log(1987 all other manufacturing employment) in eq. (1) presents problems because log(1970 own industry employment) and (1970 own industry employment)/(1970 total local employment) are also included. These variables themselves are not inordinately correlated. However, 1987 and 1970 all other manufacturing employment are very highly correlated. Thus we could be in trouble if 1970 total civilian employment and 1970 total manufacturing employment move together or form a constant ratio. In fact, they do not. For example, the 1970 ratio of manufacturing to total local employment has a one-standard-deviation interval of .13–.35 about the mean.

ian employment can be partially explained (R^2 = .31 for an ordinary least squares [OLS] regression) by exogenous regional characteristics such as regional dummies, coastline dummy, state iron ore resources, SMSA rail dummy, SMSA heating degree days, log(1970 state electricity price), and state agricultural workers. Second, for machinery, for example, if we replace log(1987 all other manufacturing) in equation (1) with its exogenous regional determinants just listed above, the coefficient of log(1970 own industry employment) is .58, which is comparable to that in table 1 and much lower than the raw persistence coefficient of .86 in table B2.

3. Endogeneity and Selectivity

As noted earlier, some of the right-hand-side variables in equation (1) listed in tables 1 and B3 are potentially endogenous. Preliminary specification tests (Smith and Blundell 1986) provided modest evidence of a problem, particularly for wages. In Henderson et al. (1992), we present two-stage estimates of the coefficients (of course, there is an issue of finding instruments not influenced by any city-industry fixed effect).[6] The two-stage estimates tend to differ in three ways. With one exception, the wage elasticity for employment in table B3 becomes much more negative. For log(1970 own industry employment), there is generally a modest drop in the coefficient, indicating reduced persistence. Finally, with one exception, the coefficient of past concentration rises in two-stage work, sometimes quite significantly. In estimation, there is also an issue of sample selection bias because, since 1970, 81 new MSAs or PMSAs have arisen that are excluded from our sample for lack of information about 1970. We conducted some two-stage Heckman-type selection tests on OLS employment regressions and found no evidence of selectivity bias.

[6] Instruments include region dummies, 1987 access to a national business center, state industrial fuel price, percentage urban in 1970, percentage 18 years or older in 1970, percentage 65 years or older in 1970, percentage of adults with 4 years of high school or some college in 1970, percentage of adults with college or more in 1970, percentage of female-headed families in 1970, percentage housed in single-family homes in 1970, percentage housed in pre-1950 housing in 1970, mean January temperature, annual rainfall, cooling degree days, 1970 distance and driving time to a national business center, railway dummy, 1970 cost of electric power by state, state farm population in 1970, percentage of manufacturing workers with no high school in 1970, percentage of manufacturing workers with college in 1970, multiple-name SMSA in 1970, state land area, regional iron resources in 1970, regional oil reserves in 1970, percentage with high school or more in 1980, percentage with college or more in 1980, and ratio of black to total population in 1980.

II. New High-Tech Industries

For the traditional manufacturing industries in Section I, there is strong evidence of MAR externalities but little evidence of Jacobs externalities. However, the analysis of dynamic externalities may differ when one looks at new or rapidly growing industries. At a two- or three-digit level it is not possible to identify entirely new industries. However, we identify three three-digit industries—electronic components, medical equipment, and computers—as having undergone sufficient transformation and growth so as to be treated as something akin to "new." Most of their marketed products for 1987 did not exist in 1970 or were not in commercial production. Employment in these industries more than doubled from 1970 to 1987.[7]

Examining these industries raises some econometric and conceptual issues. While major two-digit industries have positive employment in virtually all cities, our three high-tech industries do not. Given this, a discrete-continuous choice analysis is more appropriate than a Tobit formulation. The discrete event is whether a city has an industry or not in 1987; and, conditional on that, the continuous event is the employment level in equation (1).[8] For the discrete event, on the basis of the wage equals VMP equation from Section I, for cities with the industry ($I_{it} = 1$ vs. 0) we are estimating,

$$\text{prob}(I_{it} = 1) = \text{prob}[W_{it} < A_{it}(\cdot)f'(\tilde{N}_{it}, \ldots)P_{it}(\cdot)], \tag{3}$$

where $\tilde{N}_{it}$ is some minimal employment level (e.g., $\tilde{N}_{it} = 1$) or Inada conditions do not apply.

A. *Where High-Tech Industries Are Found*

This subsection focuses on the discrete choice analysis of where new high-tech industries chose to locate in 1987, on the basis of 1970 labor market and industrial environment conditions. What aspects of local historical industrial environments helped determine the urban winners in the race to attract and retain significant employment in high-tech industries?

Because of censoring of 1987 data, for the discrete event, we can

[7] In theory, we could subtract these three-digit components from the two-digit industries in estimation in the previous section. In practice, we could not because of data censoring (nonreporting below 250 employees) and use of employment intervals for observations censored for confidentiality.

[8] In Henderson et al. (1992), we report joint maximum likelihood estimation of the determinants of 1987 employment levels. There, MAR effects for high-tech industry employment levels are weaker than for the mature industries in table 1 since the exact concentration of the predecessor industry in many cities is less important for these industries in determining specific employment levels today.

examine only whether or not employment is greater than or equal to 250 in a city. We define this level as "significant employment." In table 3 we note that less than half of the 224 MSAs have significant employment in any of these industries, even in 1987. These industries are highly concentrated in cities such as Phoenix, Austin, Boulder, Anaheim, San Jose, Tucson, Minneapolis, Boston, and Poughkeepsie (International Business Machines) for computers and Phoenix, Dallas, Anaheim, Binghamton, Los Angeles, San Jose, Chicago, and Boston for electronic components. Some of these cities—such as Austin, Tucson, and Binghamton—had next to zero employment in these industries in 1970. Table 3 also indicates the relevant data on exit and entry in terms of significant employment. For electronic components, there is considerable mobility, both in and out. Given sufficient exits, we can look also at conditional probabilities, asking whether the way a variable affects the probability of having significant 1987 employment varies by whether the city had significant employment or not in 1970.

Probit results for wage and market condition variables for equation (3) are reported in table B4; they have expected signs. In table 4, we focus on the effects of the historical industrial environment, such as measures of predecessor own industry activity (MAR effects) and diversity (Jacobs effects). For own industry activity, since many cities in 1970 have zero activity, we focus on two measures, a dummy, I_{i0}, for significant 1970 employment (more than 249 workers) and the concentration measure for own industry 1970 employment, ρ_{i0}. For all industries in columns 1, 4, and 7 of table 4, having employment in the predecessor industry in 1970 raises the probability of having significant 1987 employment. Similarly from columns 3, 6, and 9, the greater the 1970 foothold or concentration of an industry in a city, the greater the 1987 probability of having the industry. The MAR effects definitely affect whether the city has the industry or not. To quantify effects, for a representative city (average sample values for all continuous variables) in a specific region, we calculate the effect

TABLE 3

LOCATION OF HIGH-TECH INDUSTRIES: NUMBER OF CITIES

	1970 Employment ≥ 250	1987 Employment ≥ 250	Entry: 1970 Employment < 250, 1987 Employment ≥ 250	Exit: 1970 Employment ≥ 250, 1987 Employment < 250
Computers	48	70	27	5
Electronic components	90	109	34	15
Medical instruments	64	89	39	7

TABLE 4

DETERMINANTS OF HIGH-TECH LOCATIONS: HISTORICAL INDUSTRIAL ENVIRONMENT

	ELECTRONIC COMPONENTS			MEDICAL EQUIPMENT			COMPUTERS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
I_{i0} dummy: significant employment own industry	1.305*	.412		1.450*	−.313		1.454*	1.445*	
	(.251)	(.551)		(.308)	(.732)		(.368)	(.704)	
Concentration past (ρ_{i0})			13.037			64.731			319.362*
			(8.990)			(40.123)			(146.219)
Diversity:									
Overall (D_{i0})	−4.116*	−6.125*	−6.636*	−1.860	−3.372**	−2.755	−3.223	−3.233	−3.735
	(1.754)	(2.374)	(2.150)	(1.555)	(1.893)	(1.701)	(2.143)	(2.247)	(2.295)
Conditional on significant past employment ($D_{i0} \times I_{i0}$)		7.960**	8.915*		17.976*	9.040*		.094	1.356
		(4.522)	(2.458)		(7.447)	(3.798)		(6.607)	(4.980)
Labor force in higher education or miscellaneous professionals (%)	NA	NA	NA	44.573	51.321**	61.597*	74.544*	74.547*	89.300*
				(28.986)	(30.062)	(31.286)	(35.363)	(35.364)	(36.427)

* Significant at the 5 percent level.
** Significant at the 10 percent level.

of a one-standard-deviation increase in that variable on the probability of having the industry in 1987. To quantify the effects of a dummy variable, we look at its direct impact on the representative city. For example, if our city is in the Northeast, significant employment in electronic components in 1970 (vs. not) raises the probability of having significant employment in 1987 from .30 to .80.

What about the effect of diversity? If 1970 diversity affects 1987 probabilities of attracting the industry, that suggests that Jacobs externalities are important in attracting high-tech industries. The coefficients on 1970 lack of diversity in all manufacturing (based on eq. [2] for 50 three-digit industries) are all fairly large and negative, in columns 1, 4, and 7. Strictly speaking, only one is statistically significant; however, the others are significant at not unreasonable levels. For electronic components, for a representative city in the Northeast without significant 1970 employment, a one-standard-deviation *decrease* in lack of diversity increases the probability of 1987 employment from .30 to .44. But that is not the whole story.

For the diversity measure, we also looked at conditional probabilities, where we allow the slope coefficient to vary with whether the city had significant 1970 employment or not.[9] For high-tech industries in columns 2, 5, and 8, cities without the industry in 1970 have large negative (and reasonably significant) coefficients for lack of diversity. For cities with the industry in 1970, there is generally an offsetting positive effect. For example, for electronic components, for cities in the Northeast without the industry in 1970, a one-standard-deviation decrease in 1970 lack of diversity increases the city's probability of having the industry in 1987 from .44 to .64. Yet, for cities with the industry in 1970, the net coefficient is actually nonnegative, with the impact on probabilities of a change in diversity being negligible. Given the lower number of exits for computers and medical instruments, it is hard to have confidence in the precise conditional results, but the same pattern appears. For all industries, results in columns 3, 6, and 9 are similar to those in columns 2, 5, and 8.[10]

These results suggest a particular twist to Jacobs externalities. They are important for a city's ability to initially attract new industries: diversity provides a fertile breeding ground for childless cities. But they are unimportant for retaining these industries: prior concentration of the own predecessor industry is what matters.

[9] For electronic components, no other variables for differential slope coefficients were close to being significant.

[10] For electronic components we also experimented with two-stage estimation and found no strong effects. For example, if we treat the dummy variable for significant 1970 employment as endogenous in col. 1, the diversity coefficient remains unchanged.

Finally we note that in table 4 for computers and medical equipment, cities with higher concentrations of workers in higher education and miscellaneous professionals also had higher probabilities of having the industry in 1987. This group of people represents the importance to computer and instrument development of interaction with the local basic and applied research sectors of the economy, representing dynamic spillover benefits for our industries. So, for example, for a city in the Northeast without significant 1970 employment, a one-standard-deviation increase in the proportion of higher education and miscellaneous professionals raises the probability of having computers in 1987 from .21 to .31. A similar force may be at work in table B4, where the percentage of adults with a college degree takes on heightened importance, compared to mature industries in table B3. For example, for a Northeast city with no 1970 computers, a one-standard-deviation increase in the proportion of the college-educated population raises the probability of having computers from .21 to .43.

III. Conclusions

Dynamic externalities come from local accumulations of knowledge enhanced by long-term relationships and histories of interactions, creating a stock of "local trade secrets" that benefit local firms. Cities provide a natural laboratory to study the nature and extent of these externalities. In this paper we examined employment growth rates for five key traditional capital goods industries. For these industries we observe a very high degree of persistence in employment patterns. While persistent regional demand and comparative advantage explain some of this, MAR dynamic externalities are critical also. In particular, employment growth in traditional manufacturing industries is higher in cities with high past employment concentrations in the own industry. A history of industrial diversity did not have a significant effect on any of these traditional industries, except for instruments, suggesting that Jacobs externalities are not so important for mature industries.

For newer high-tech industries, we do not focus on persistence since the industry is new. We observe very rapid growth, both in the number of cities hosting a particular industry and in employment levels within those cities. It is natural to ask which historical environments have an advantage in the ongoing race to attract newer industries. Unlike the traditional manufacturing industries, high levels of past industrial diversity increase the probability that a city will attract a high-tech industry. This suggests that Jacobs externalities play an important role in the development of the high-tech sector. But MAR externalities were also found to play a role in the development of the high-tech sector. In particular, while Jacobs externalities are important in attracting new industries, MAR externalities, rather than Jacobs externalities, are important for retaining the industry.

Appendix A

Data Sources and Definitions

1987 Variables

Employment data are taken from the 1987 *Census of Manufactures* supplemented by 1987 *County Business Patterns* (CBP) data. For some cities, 1987 *Census of Manufactures* data are censored for disclosure reasons and give employment figures in intervals. Because the upper open-ended interval starts at just 2,500, these employment data are supplemented with 1987 data from CBP (with appropriate adjustments so 1987 CBP definitions of Standard Industrial Classification 36 and 38 correspond to *Census of Manufactures* definitions). The CBP employment data are less likely to be censored and to have a much more extensive set of intervals for censored data, with the upper open-ended interval starting only at 100,000 employees.

Socioeconomic data are taken from the 1986 *State and Metropolitan Area Data Book* (Bureau of the Census). Access data are based on Rand McNally's 30 national business centers in 1990. National business centers are market centers defined by volume of transactions.

The variables used and their mean and standard deviation are defined as follows.

Manufacturing wage ($000s): average income of production workers in 1982 (mean 17.4; s.d. 3.6).
Percentage of adults with at least high school, for the 1980 population over 25 (mean 0.68; s.d. 0.08).
Percentage of adults with at least college, for the 1980 population over 25 (mean 0.16; s.d. 0.05).
Distance to national business center; straight-line distance (mean 1.71; s.d. 3.29).
Total manufacturing employment (000s) for 1987 (mean 58.4; s.d. 100.8).
Diversity index, for 1987 (mean 0.17; s.d. 0.24 [excludes machinery]).
Regional Northeast, Midwest, and South dummy variables have means of .18, .29, and .35, respectively.

1970 Variables

Employment data are taken from 1970 *Census of Population* Sixth Count Table 1270 on employment by SMSA. Socioeconomic data are taken from the 1972 *City and County Data Book* and the 1972 *Census of Manufactures*.

The variables used and their mean and standard deviation are defined as follows.

Manufacturing wage: average hourly wage of production and nonproduction workers for 1972 (mean 4.6; s.d. 3.6).
Concentration of machinery for 1970 (mean .026; s.d. 030).
Concentration of electrical machinery for 1970 (mean .024; s.d. .033).
Concentration of primary metals for 1970 (mean .023; s.d. .041).
Concentration of transportation for 1970 (mean .022; s.d. .031).
Concentration of instruments for 1970 (mean .0041; s.d. .013).
Concentration of electronic components for 1970 *County Business Patterns* (mean .011; s.d. .026 for 207 metro areas).
Concentration of computers for 1970 (mean .002; s.d. .006 for 207 metro areas).
Concentration of medical equipment for 1970 (mean .0025; s.d. .0099).
Total manufacturing employment (000s) for 1970 (mean 58.8; s.d. 110.8).
Percentage of labor force in higher education and miscellaneous professionals for 1970 (mean .019; s.d. .004).
Total employment (000s) for 1970 (mean 219.1; s.d. 368.3).
Percentage of adults with at least high school for the 1970 population over 25 (mean .55; s.d. .08).
Percentage of adults with at least college for the 1970 population over 25 (mean .11; s.d. .04).
Diversity index for 1970 for 50 manufacturing industries (mean .12; s.d. .08 [excludes electronic components]).

Appendix B

TABLE B1

INDUSTRY EMPLOYMENT PATTERNS ACROSS 224 METROPOLITAN AREAS

	Machinery	Electrical Machinery	Primary Metals	Transportation	Instruments
1970 number of cities with zero employment	0	0 (33)	1	0	5 (64)
1970 number of cities with over 249 employees	196	176 (158)	152	168	102 (108)
1987 number of cities with over 249 employees	206	175	146	166	133
1970 mean employment	6,667	6,504	4,211	7,833	1,344
1970 mean employment in cities with over 249 employees	7,598	8,251	6,133	10,405	2,869
1987 mean employment in cities with over 249 employees	6,948	6,801	3,706	9,180	6,081

SOURCE.—Except for electrical machinery and instruments, all 1970 numbers are taken from the *Census of Population* and all 1987 numbers are taken from the *Census of Manufactures*. For electrical machinery and instruments, the numbers in parentheses are taken from *County Business Patterns*.

NOTE.—Different censuses record different levels of specific types of economic activity. The *Census of Population* tends to be broader-based because it incorporates home production; the *County Business Patterns* and *Census of Manufactures* deal with the formal sector. (How would the activities of Steven Jobs and Stephen Wozniak have been classified in 1976?) Differences in the industrial classification schemes and errors in self-reporting also create differences in the numbers.

TABLE B2

(NON-)CONVERGENCE ACROSS METROPOLITAN AREAS

$$\log(Y_{87}/Y_{70}) = -\delta \log Y_{70} + \ldots$$

	δ	$1 - \delta$	β (%)*	Observations
Total manufacturing employment	.058	.942	.35	224
Per capita manufacturing employment	.061	.939	.37	224
Machinery employment	.136	.864	.85	207
Electrical machinery	.204	.796	1.34	207
Primary metals	.192	.808	1.25	207
Transportation equipment	.127	.873	.79	207
Instruments	.193	.807	1.26	207
Wage rate	.743	.257	7.99	207

NOTE.—Equations for total and per capita manufacturing are estimated as specified by OLS. Standard errors on δ are, respectively, .020 and .054. Equations for individual industries are estimated by Tobit (given that 1987 data are censored) in the form $\log Y_{87} = \alpha + (1 - \delta)\log Y_{70} + \ldots$. Coefficients of $1 - \delta$ have standard errors of, respectively, .029, .035, .045, .042, and .052, so t-statistics are all over 15.0. Included in the estimating equations are regional dummies.

* β is the annual rate of convergence (percentage) and is the solution to $\delta = 1 - e^{-\beta T}$ for $T = 17$ years. In contrast to overall manufacturing employment persistence, for manufacturing wages there is strong convergence, so $\beta = 7.99$ percent.

TABLE B3

DETERMINANTS OF LOG(1987 OWN INDUSTRY EMPLOYMENT): MARKET CONDITIONS (N = 207)

	Machinery	Electrical Machinery	Primary Metals	Transportation	Instruments
	Regional Demand				
Intercept	−2.171*	.594	−2.706*	−2.607	1.004
	(.798)	(1.153)	(1.301)	(1.639)	(1.593)
Region:					
Northeast	−.422*	−.678*	.083	−.508**	−.279
	(.152)	(.212)	(.224)	(.284)	(.301)
Midwest	−.356*	−.497*	.530*	−.048	−.299
	(.137)	(.182)	(.193)	(.247)	(.259)
South	.046	−.085	.442**	.288	−.359
	(.145)	(.208)	(.232)	(.283)	(.304)
Distance to national business center	−.045*	−.047*	−.025	−.020	−.130**
	(.014)	(.022)	(.032)	(.023)	(.071)
Log(all other manufacturing employment)	.357*	.223*	.310*	.986*	.641*
	(.074)	(.086)	(.078)	(.058)	(.123)
	Local Labor Markets				
Log(manufacturing wage)	−.939*	−1.534*	−.772**	−.626	−2.345*
	(.241)	(.346)	(.396)	(.500)	(.539)
Adults with at least high school (%)	2.015*	−.107	.851	.044	4.095*
	(.990)	(1.387)	(1.602)	(1.94)	(2.069)
Adults with college (%)	2.678*	5.551*	−2.159	2.350	2.196
	(1.223)	(1.721)	(2.028)	(2.465)	(2.486)
Adjusted R^2 (OLS)	.870	.804	.763	.728	.726

NOTE.—Standard errors are in parentheses. The sample size is reduced from 224 to 207 because of missing observations on wages.
* Significant at the 5 percent level.
** Significant at the 10 percent level.

TABLE B4

OTHER DETERMINANTS OF HIGH-TECH LOCATIONS (N = 224)

Market Conditions Historically	Electronic Components	Medical Instruments	Computers
Constant	−5.354*	−6.856*	−13.444*
	(1.886)	(1.931)	(3.040)
Region:			
Northeast	−.771	−.749	.367
	(.483)	(.511)	(.499)
Midwest	−1.062*	−.689**	−.668
	(.375)	(.411)	(.436)
South	−.847*	−.537	.453
	(.430)	(.452)	(.515)
Distance to national business center	.0011	−.0004	.0006
	(.0006)	(.0007)	(.0007)
Adults with at least high school (%)	−2.916	−5.963*	8.104*
	(2.552)	(2.649)	(3.496)
Adults with college degree (%)	15.169*	16.897*	6.874
	(4.198)	(4.695)	(5.268)
Log (manufacturing wage)	−.280	−.500	−.479
	(.436)	(.522)	(.432)
Log (all other manufacturing employment)	.603*	.829*	.648*
	(.134)	(.154)	(.174)
Predicted correctly (%)	84	83	86

NOTE.—Results correspond to the equation for cols. 1, 4, and 7 in table 4.
* Significant at the 5 percent level.
** Significant at the 10 percent level.

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