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Spatial evolution of the computer industry in the USA

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Abstract

This paper examines the spatial evolution of computers across 317 metro areas in the USA since the introduction of the personal computer. We start by examining the relative distribution of employment across cities, examining how that distribution changes in 1977–1992 and how cities move through the distribution. For computers, transition matrices are stationary, with the industry exhibiting no tendency to settle down, nor any tendency of retrenchment during periods of national high-tech employment decline. There is no tendency of the relative size distribution of computer employment to collapse, go bimodal, etc. Overall computers exhibit some turbulence, with dramatic big winners and losers among cities, as well as persistence for some cities in employment shares. In attracting or repelling an industry, urban heterogeneity is important. Large, well educated cities near San Jose have a much greater chance of attracting high-tech employment (much lower mean first passage times moving up states) and less chance of losing it. In assessing the determinants of persistence in local employment patterns we examine sources of productivity growth. We find strong evidence of significant dynamic own industry externalities for single plant firms and little evidence of urbanization-Jacobs-knowledge type externalities. Corporate plants in computers seem to be self-reliant and not really influenced by externalities.

JEL classification: L86; R39

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0. Introduction

In the race by cities to attract high-tech industries, what have been the characteristics of winners and losers and how secure is the position of the initial winners? Is a city more likely to attract large high-tech employment if it has an educated labor force, low wages, a diverse industrial base, an attractive tax policy, or a history of employment in related industries? If it is successful in attracting high-tech employment, what factors influence how likely is it to retain that employment? While these questions are of intellectual interest for reasons we will discuss next, they are also policy relevant. Many localities around the world over the last 20 years developed policies and dedicated considerable public resources to trying to attract high-tech industries. Which of these localities in the USA had, a priori, the best chances of success?

In thinking about such questions, there are several relevant literatures and conceptual frameworks. The traditional empirical location literature presumes a high degree of industrial mobility (e.g., Bartik, 1988; Carlton, 1983; Henderson, 1994; Herzog and Schlottman, 1991; Papke, 1991). Even for industries with steady national employment each year a significant fraction of plants and firms die – 5–10% – to be replaced by a wave of births. The choice of new plant locations is modeled as a process where owners survey the national landscape and pick the profit-maximizing location, given observed and unobserved firm attributes. Empirical work focuses on the choice of covariates reflecting a location's attractiveness, with a particular focus on tax and labor market conditions. While scale measures such as total metro area employment or own industry employment stocks are considered, they are simply two of many attributes affecting location decisions of new plants in the traditional literature.

In contrast, a more recent theoretical literature stresses persistence and inflexibility of locational patterns, with a strong role for historical accidents, generally based on accentuating the role of historical own industry scale. For example, in his key work Arthur (1990) develops a firm–location matching model of the evolution of industry location. Heterogenous firms enter the national market in sequence choosing among heterogenous locations, where a key element in perceived profits is accumulated own industry scale providing external scale benefits in the form of information spillovers. In such a world, locations that are inherently inferior for most firms can emerge as long-term winners if they accumulate 'by accident' (through order of entry of heterogenous firms) early stocks. Arthur predicts that as an industry evolves, local relative employment fluctuations will dampen, and locational patterns measured by locational shares of national industry employment will become fixed. This notion of persistence and inflexibility of location patterns is furthered in Rauch (1993) and Mitra (1995), who model inflexibility as deriving from dynamic externalities. If local productivity today in an industry is affected by own industry scale a year ago (a dynamic externality) that makes it very difficult for locations with little or no history of the industry to attract plants, since, for example, they have no builtup stock of local trade secrets (the dynamic externality). In contrast, with static externalities, if plants move from one location to another en masse, no scale benefits are lost. Finally, while Arthur is focussed on industrial expansion, other scale economy based papers by Adsera (1996) and Henderson (1986) suggest that, with national industrial contraction, there will be a reconsolidation, with some regions losing the industry.

This recent theoretical literature and the traditional empirical literature seem to part company in two key ways. First is the role of scale economies versus changing local comparative advantage. The theoretical models fix regional characteristics, do not consider relative regional shocks, and give scale economies a key role leading to inflexibility in locational patterns. In the traditional empirical literature, changing regional characteristics and unobserved regional shocks will, in essence, reshuffle the deck, potentially causing changes in locational patterns and creating fluidity. Second, the traditional location literature and an associated traditional literature on productivity and local externalities (Sveikauskas, 1975; Nakamura, 1985; Henderson, 1988; Ciccone and Hall, 1996) in considering scale externalities assume they are static, rather than dynamic. The theoretical literature stresses more the role of dynamic externalities, since they are potentially a key source of locational persistence. Some preliminary empirical work on them exists in Glaeser et al. (1992) and Henderson et al. (1995).

In this paper, by examining the spatial evolution of computer industry employment and impacts on productivity, we seek to obtain information on three issues. First, we examine the question of locational fluidity directly, to get a sense of the revelance of the recent theoretical literature. Do fluctuations in location patterns dampen over time as Arthur predicts? With national retrenchment, does employment reconsolidate into fewer locations? Or do employment patterns appear relatively fluid with on-going reshuffling? Second, consistent with the focus of the traditional literature, we examine what observed locational characteristics strongly influence locational patterns. We consider factors such as local labor market conditions, state taxes, local industrial diversity, employment in related industries, nearness of locations to other centers of high-tech employment and the like. This will allow us to develop a profile of 'superior' sites, relative to ordinary ones, to get a sense of which cities would a priori be expected to be winners in the high-tech race. Examining these first two issues will also tell us a lot about spatial development of the computer industry, a topic of interest in and of itself.

Third, we examine two items of concern in the externality literature. We analyze productivity growth in plants for evidence of own industry externalities, distinguishing single plant firms from corporate plants who may rely more on internal firm information networks. The econometric work will test for and quantify the magnitude of any static versus dynamic own industry externalities,

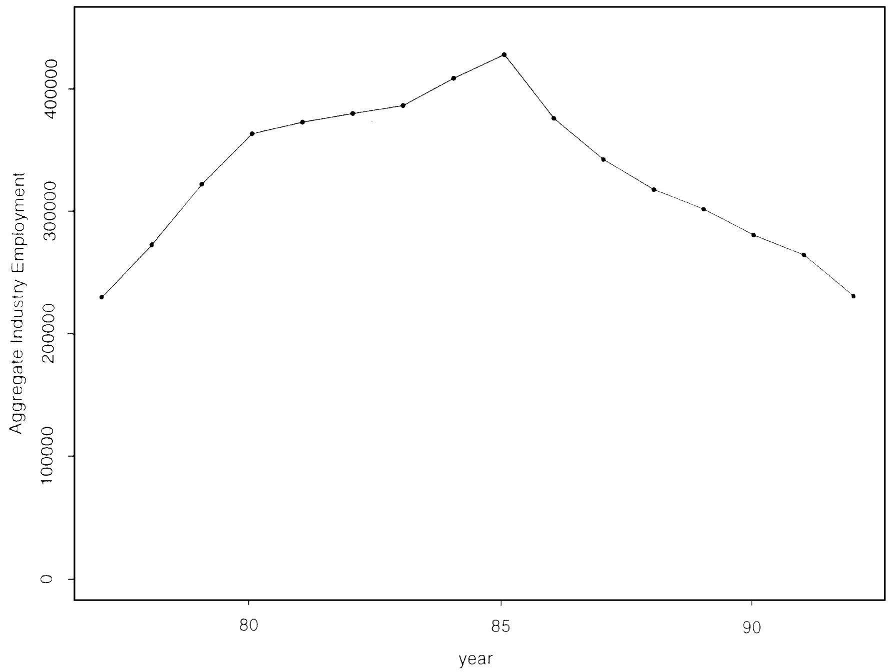

Fig. 1. National urban computer employment (SIC 357).

giving evidence about the potential importance of such externalities. We will also look for evidence of urbanization, or Jacobs externalities which the recent empirical literature considers important. The Jacobs hypothesis is that local diversity of the industrial environment fosters a creative context with cross industry fertilization of ideas that could be important to local emerging high-tech industries such as computers.

In the paper, spatial evolution and productivity are examined in the computer industry[1] for 1977–1992. The time period and industry are ideal. 1977 dates the first marketing of personal computers. The date is a takeoff point for the computer industry and a transformation point as the industry shifts towards a new product, PCs. As Fig. 1 indicates, from 1977 to 1985, national urban computer employment (which accounts for over 90% of national computer employment) doubled nationally, with production diversifying away from IBM

[1] Computers includes all processing, hard drive, and storage devices, terminals, and all peripheral equipment for computers per se (scanners, printers, etc.), as well as office machinery such as ATMs, cash registers, collaters, etc.

into a variety of new firms. In examining evolution of the industry, we want to learn what determined which cities gained new employment in this redefined industry and what main-frame cities lost out versus capitalized on their initial position. The issue is dramatized by the subsequent decline in national computer employment between 1985 and 1992, such that 1992 employment levels are back to 1977 ones, albeit in a transformed industry. The 1985–1992 decline reflects both technological change with increased capital intensity in computers and a drop in real shipments from USA plants (from \$56.1b to \$47.6b) as production moved offshore. This decline allows us to evaluate the impact of national retrenchment and to assess the characteristics of emergent winners, in the struggle to retain initial high-tech gains.

In examining our three issues, the paper is divided into two sections. Section 1 examines the spatial evolution of computer employment. We first examine the raw data, looking for evidence on fluidity, dampening of changes in employment patterns and retrenchment effects, relevant to the recent theoretical literature. Then we examine changes in employment patterns to determine the characteristics of likely winners versus loosers, the concern of the traditional empirical literature. Data are annual County Business Patterns data (CBP) of the US Census Bureau for 1977–1992 on employment by all private establishments[2] for regions defined as the 317 (Primary) Metropolitan Statistical Areas (MSAs) of the USA based on the 742 urban counties as of 1990. Section 2 of the paper turns to estimation of dynamic externalities. Estimation is for establishments in the 1984–1988 wave of the Annual Survey of Manufacturers as contained in the Longitudinal Research Data base of the US Census Bureau. Individual establishment data on productivity are combined with CBP data on the current and historical industrial environment of cities, to look for evidence of dynamic externalities of the local industrial environment on establishment productivity.

1. Spatial evolution

To characterize evolution of the computer industry, we examine the distribution of relative employment across cities in 1977 and how that distribution changes over time to 1992. We analyze the raw and conditioned transition process of cities moving through the distribution, as opposed to simply analyzing the determinants of individual city employment levels. Examining the

[2] The employment data have been 'massaged' based on an algorithm of Gardocki and Baj (1985) of the Center for Government Studies of Northern Illinois State University to fill in numbers for those few censored locations where employment is reported in intervals. Point estimates are based on regional and industry adding up constraints.

overall distribution and modeling how cities move through the distribution allow us to directly address the issues posed in the recent theoretical literature. We can examine transition matrices to (1) test for stationarity – dampening or acceleration in mobility rates, (2) analyze fluidity in terms of mean first passage times, and (3) characterize evolution of the employment distribution across cities to determine if it is 'converging'/collapsing, spreading, going bimodel, etc. We can then condition the transition process to determine what urban characteristics make it more likely for a city to move up in the distribution – emerge as a winner – or to retain an initial high position.

1.1. The basic patterns

In looking at the data, we assume distributions evolve over time according to a homogenous stationary first-order Markov process from 1977 to 1992. For M the transition matrix and f the distribution, then

$$f_{t+q} = M^q f_t \,. \tag{1}$$

Stationarity is tested for in the raw data and homogeneity is relaxed below in estimation through conditioning transition probabilities. The first-order process is a technical simplification to allow us to approximate evolution. Stationarity will be tested for and heterogeneity modeled later on. A Markov process may be objected to. For example, it implies every city, even inherently inferior locations, at some point will occupy each cell of the distribution even if in practice it takes centuries to get to the highest cell and, once there, a city may quickly drop to lower cells. However, as an approximation, a Markov process is a convenient analytical device to directly model fluidity.

Apart from examining transition matrices to get a sense of speed at which locations move through the distribution, we look at mean first passage times, for a process starting at time zero. If ϕ^t_{jk} is the probability that a city in state j (cell j in the distribution) next first visits state k at a time t periods later, then the mean first passage time, mp_{jk}, from j to k is

$$mp_{jk} = \sum_{t=1}^{\infty} t\phi^t_{jk} \,. \tag{2}$$

In our calculations mp_{jk} will be bounded. We define $[M^t]_{jk}$ as the j, k element of the transition matrix raised to the power t. Then for ϕ^t_{jk}, we note that Markov chain theory gives the t-period transition probabilities as

$$[M^t]_{jk} = \sum_{s=0}^{t} \phi^s_{jk}[M^{t-s}]_{kk} \quad \forall t \geq 1. \tag{3}$$

Table 1
Evolution of the distribution of computer employment

Cell	Upper cutoff [a] point (relative to mean employment)	Distributions (percent in cell)			
		1977	1985	1992	Ergodic
A. Cell cutoffs and distributions					
f1	0.0016	56	56	39	41
f2	0.192	16	12	31	23
f3	2.88	18	24	21	26
f4	Open	10	7	9	10
B. Transition matrix					
$t+1$					
		1	2	3	4
t	1	0.905	0.086	0.0083	0.0004
	2	0.151	0.780	0.068	0.0010
	3	0.012	0.061	0.890	0.037
	4	0	0.0024	0.102	0.895
C. Mean first passage times					
		1	2	3	4
Initial state	1	(2.5)	12.4	39.2	125.3
	2	13.9	(4.3)	31.5	117.9
	3	29.8	20.2	(3.8)	88.5
	4	39.0	29.3	10.3	(10.3)

[a] For this cell division the absolute cutoff points in 1977 are 1.15, 137.6, 2064.8, open employees.

Given $\phi^1_{jk} = [M]_{jk}$ and $\phi^0_{jk} = 0$ we can use Eq. (3) to recursively define ϕ^t_{jk} as (see Karlin and Taylor, 1975)[3]

$$\phi^t_{jk} = [M^t]_{jk} - \sum_{s=0}^{t-1} \phi^s_{jk}[M^{t-s}]_{kk}, \quad \forall t \geq 1. \tag{4}$$

Table 1 presents basic results. Table 1A lists the initial (1977) and last observed (1992) relative size distributions with cell cut off points, as well as a calculation of the ergodic distributions, done to examine any tendency for the distributions to collapse or spread. The table uses a cell division, which is constructed to isolate the tails. We work with a four cell discrete distribution of city computer employment relative to mean national high-tech employment

[3] In Eq. (4), the first term reflects the probability of all paths leading from j at zero to k at t, including paths passing through k one or more times prior to time t. The second term adjusts the first downward, to account for paths which started at j but visited k prior to t. That leaves ϕ^t_{jk} as the probability that k is first visited at time t, starting in j at time 0.

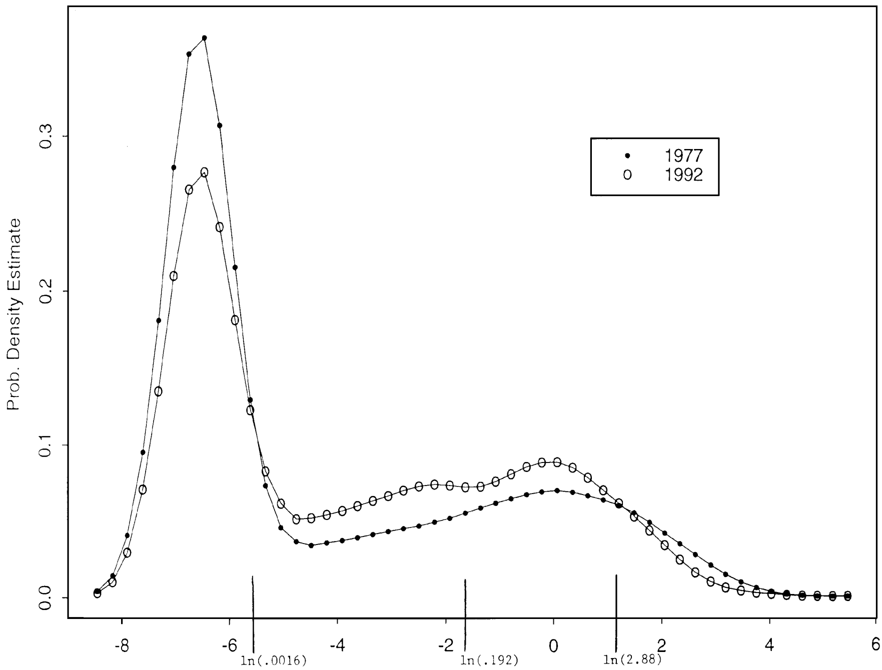

Fig. 2. Prob. density function for relative local computer employment.

across cities,[4] restricting ourselves to four cells to ensure sufficient sample size in cells to estimate conditional transition models (see later). We looked also at five and six cell divisions of the distribution, getting similar outcomes. A lower cell cutoff of 0.0016 corresponds to MSAs with one employee or less – in 1977 this comprises 172 cities with zero employment and seven with one. An upper cell cutoff corresponds in 1977 to 2065 employees minimum for the last cell, for which 31 MSAs qualify in 1977. Fig. 2 illustrates the density functions for 1977 and 1992 logs of relative computer employment, illustrating how the cutoff points bracket sections of the distribution. Results are robust to choice of precise cutoff points. Note distributions of absolute employment levels are identical in shape to those in Fig. 2; standardizing to get relative employment levels only changes units on the horizontal axis.

Table 1A gives two immediate results. First during the period, 1985–1992, of rapid decline for computers, rather than relative retrenchment, more cities move

[4] The median is typically zero or close to zero, so using the mean (or equivalently total national) employment appears to be the best way to standardize.

out of the lowest state into a higher state. More locations gain high-tech; and, as such, there is not consolidation with retrenchment. This suggests factors such as evolving marketing and distribution processes dominated the scale-retrenchment considerations of the theoretical literature. For example in the 1985–1992 time period, as computer usuage became more widespread, small scale local assemblers and parts manufacturers may have developed to service regional market niches and to aid in the local distribution process for major manufacturers. Second, the calculations of the ergodic distribution (M^t, $t \to \infty$ approximated by $t = 1000$) suggests no tendency of the distribution to collapse or go bimodal, and suggests a limit to how much the distribution will spread out. Even in the long run we can expect 40% or so of cities to have virtually no employment in computers. That, of course, does indicate own industry scale effects still do play an important role, fostering agglomeration.

Table 1B shows the maximum likelihood estimates of the transition probabilities. The estimate of any element, P_{ij}, is simply the total number of cities moving from i in year t to j in year $t+1$ summed over all 15 years of transitions divided by the total sum of cities ever in i over the 15 years. Table 1B gives two more results. Stationarity of transition probabilities is tested against non-stationarity (different year-to-year probabilities) for 1977–1992 and also for two subtime periods, the period of expansion 1977–1985 and the one of contraction 1985–1992. In no case is stationarity close to being rejected.[5] For computers, even years of most rapid expansion nationally (1978–1979) or rapid decline (1985–1986) have very similar transition probabilities, as other years.

Stationarity indicates that no 'settling down' occurs, in contradiction to what a simple Arthur model would predict. Cities continue to transit through the relative size distribution at the same rates throughout, perhaps suggesting on-going local and establishment shocks drive much of the process. Thus national expansion and contraction of computer employment occurred to some extent 'across the board', driving up and then down absolute employment levels at different locations (allowing for transiting of many of these locations), with little impact on the overall relative size distribution.

Second in Table 1B, we can start to examine the issue of fluidity. As expected the diagonal transition probabilities for staying in the own state are high, indicating that, if you start in start i, a year later the probability you will be in

[5] The χ^2 statistic is

$$-2\log\left\{\Pi_t \Pi_i \Pi_j \left[\frac{\hat{P}_{ij}}{\hat{P}_{ij}(t)}\right]^{M_{ij}(t)}\right\}$$

with $(T-1)K(K-1)$ degrees of freedom. $\hat{P}_{ij}$ is the stationary estimate; $\hat{P}_{ij}(t)$ are the year-to-year estimates; $m_{ij}(t)$ is the number of cities moving from i to j in year t; T is the total number of years and K the number of cells in the distribution. For two sets of cell divisions and three sets of time periods, the lowest p-value (mass remaining in upper tail) encountered was 0.42.

state i at least 0.78, with probabilities of about 0.9, for the highest and lowest states. So, at least, from any starting state there is a degree of persistence as would be expected given immobility of existing plant capital, as well as static or dynamic own industry externalities. But how high is the degree of persistence? We are going to argue not very high.

The transition probabilities are year-to-year ones. So if a city is in highest state, in fact you have a 0.10 chance of being in a lower state just one year later. The diagonal probabilities are far from being close to one. One way to view the issue of fluidity is to examine mean first passage times. In Table 1C, we present mean first passage times, which are truncated at $t = 1000$ (with calculated times essentially unchanging by $t = 500$). For cities in less than the highest cell, transition to next having large computer employment is expected to take, 9–13 decades, from the current state to state 4. Movement up is considerably slower than movement down. (The diagonal elements in parentheses can be interpreted as mean first return times. First return involves staying in the own cell for one period or first returning to the own cell if a city exited in the first period.) So how slow is 9–13 decades to move from a lower state to the highest state? If the diagonal transition probabilities were all 0.99 (with immediate off diagonal elements 0.01 for states 1 and 4 and 0.005 states 2 and 3), the mean first passage times of moving to the highest state would be 22–33 decades. For diagonal elements of 0.95 where a city in the highest state still has a 0.05% chance within a year of falling from that state, the corresponding numbers are 10–18 decades. Computer movements up are quicker than that and movements down are much faster. In the hypothetical symmetric transition matrices cited, movement to the lowest state from other states symmetrically takes 22–33 (for 0.99 diagonals) or 10–18 (for 0.95 diagonals). For computers we are talking about only 1–4 decades, based on our transition probabilities. This is substantial fluidity, in contrast to Arthur's notion of fixed positions.

In summary, the concerns of the recent theoretical literature do not seem that relevant. There is no dampening in movements over time, no consolidation with retrenchment, and a limited degree of persistence. The situation seems relatively fluid with, perhaps, local shocks fermenting on-going change. The national employment distribution seems fairly stable with no tendency to converge/collapse or to go bimodal.

In learning about the complete industry itself, state 4 is of considerable interest since it accounts for a high proportion of national employment – over 80% in computers in 1977. State 4 contains the 'winners' – cities with big agglomerations. In Table 2, we focus on the winners and losers, where in the years following the invention of PCs, there is considerable turnover and turbulence among these cities. Looking at the eight biggest employer cities, half turn over between 1977 and 1992, with entry of some western and southern MSAs. With the exception of the entry of Austin and exit of LA, within the top five, however, there is no change. But the columns on big losers and winners are the

Table 2
Dominant computer cities (employment in 1000's in parentheses)

Eight biggest employers				Big losers (1992 employ. less than 50% of 1977, given 1977 employ. over 2000) (1977, 1992 employ. in parentheses)		Big winners (1992 employ. greater than 2000, grows by 50% over 1977) (1977, 1992 employ. in parentheses)		Flash-in the-pan (with 1977, 1985 and 1992 employ.)	
1997		1992							
San Jose	(26.2)	San Jose	(38.5)	Cleveland	(2.5, 0.8)	Austin	(2.8, 13.2)	Colorado Springs	(0.3, 3.3, 1.3)
Minneapolis	(16.6)	Austin	(13.2)	Dallas	(7.0, 2.5)	Boulder	(2.7, 5.8)	Oxnard, CA	(0.2, 2.0, 0.2)
Boston	(13.5)	Boston	(13.0)	Dayton	(2.5, 0.4)	Oakland	(2.4, 5.8)	Manchester, NH	(0.3, 3.2, 1.3)
Los Angeles	(11.9)	Orange County	(10.9)	Detroit	(3.3, 0.3)	Oklahoma	(1.8, 3.1)	Rochester, NY	(0.95, 2.8, 0.2)
Orange County	(11.0)	Minneapolis	(7.1)	Los Angeles	(11.8, 4.2)	Long Island	(1.7, 2.9)	Spokane	(0.7, 3.5, 1.2)
Poughkeepskie, NY	(8.4)	San Diego	(6.0)	Minneapolis	(16.6, 7.1)	Boise	(0.4, 5.0)	DC	(0.6, 3.6, 1.4)
Chicago	(7.7)	Huntsville, AL	(6.0)	Nashua, NH	(2.1, 1.0)	Atlanta	(0.3, 2.4)	Tuscon	(0.4, 7.5, 0.2)
Worchester	(7.6)	Raleigh	(5.9)	Philadelphia	(6.1, 2.1)	Eau Claire, WI	(0.2, 2.5)		
				Phoenix	(7.1, 1.3)	Ft. Collins	(0.02, 2.5)		
				Santa Barbara	(2.3, 0.9)	Ft. Worth	(0.03, 2.5)		
				Utica, NY	(3.1, 0.4)	Huntsville	(0.3, 6.0)		
				West Palm Bch.	(2.5, 0.08)	Portland	(0.2, 3.8)		
				Worchester, MA	(7.6, 1.8)	Sacramento	(0.1, 2.6)		

most telling. Traditional mainframe centers in mid-Western and North-Eastern states experienced big losses, along with some major metro areas elsewhere – LA and Dallas in particular. With a few exceptions winners are western and some southern cities. In the winner column, the first five entries are cities which expanded from a reasonable 1977 base. The other eight are the high-tech 'miracles' – places with little history of computers but significant 1992 employment. This period of turbulence also saw initial big gainers in the 1977–1985 expansion in the last column of Table 2, who ended up with little employment under retrenchment.[6]

1.2. Parameterizing transition probabilities

So far we have examined the basic data for transition processes, treating cities as homogenous. Now we treat them as heterogenous and condition the transition process to determine sources of heterogeneity. We look for covariates that increase of city's chances of moving up states or remaining in higher states. Each element of the transition process, P^s_{ij}, giving the probability of city s transiting from state i and j between t and $t+1$ is given by a function $g_{ij}(X_s\beta)$ for X_s a set of exogenous covariates and β parameters, where $\sum_{j=1}^{K} g_{ij} = 1$, for K the number of cells. Thus in estimation, each row in Table 1B involves a separate estimation for each initial state i, giving city specific probabilities of moving from that i to any other (plus the own) state.

A natural choice of specification is the multinomial logit where

$$P^s_{ij} = \frac{\exp(X_s\beta_{ij})}{1 + \sum_{j\neq i}^{K} \exp(X_s\beta_{ij})}, \quad j = 1,\dots,K, \quad j \neq i, \tag{5}$$

$$P^s_{ii} = \frac{1}{1 + \sum_{j\neq i}^{K} \exp(X_s\beta_{ij})}.$$

[6] An issue concerning Table 2 is whether very large plants dominate the process for losers, miracle winners or flash-in-the-pan cities). First, we note two facts. Average plants sizes in computers in 1992 are about 60% smaller than in 1997. Second, from a county fixed effect regression of the ln(average plant employment) on time dummies and ln(total MSA employment), the coefficient on ln(total MSA employment) is positive (0.940), and strongly significant, indicating average plant sizes increase (not decrease) as we move to the really big cities. In terms of Table 2, for all the cities in the loser category, while collective employment falls from 75,000 to 24,000, the number of establishments rises from 278 to 378, with the numbers of plants with over 1000 employees falling, respectively, from 20 to 2. For big winners, total employment rises from 13,000 to 58,000 and the number of plants goes from 102 to 284, with the number of plants over 1000 employees rising from 3 to 15. Similarly, flash-in-the-pan cities go from 0 cities with over 1000 employees in 1977, to 7 in 1985, and back to 0 in 1992. In summary these types of numbers suggest large plant movements do play a role in employment swings but do not dominate the process. Moreover, there is enormous heterogeneity. For 1992, our big winners, Austin, Boulder, Oakland, Oklahoma, Long Island, Boise, Atlanta and Huntsville, AL have average plant sizes of, respectively, 385, 232, 73, 282, 107, 833, 69, and 1500.

In this formulation, coefficients of the own state are set equal to zero to normalize and identify the other coefficients. Given the model based on Eq. (5) is estimated separately for each i, we are estimating the determinants of probabilities of moving from i to j, conditional on starting in i. Parameters have a difficult direct interpretation, where

$$\frac{\partial P^s_{ij}}{\partial X_s} \bigg/ P^s_{ij} = \beta_{ij} - \sum_{j=1}^{K-1} P_{ij}\beta_{ij}\,. \tag{6}$$

In practice, since the P_{ij} are off diagonal probabilities they are small, so in Eq. (6), $(\partial P^s_{ij}/\partial X_s)/P^s_{ij} \approx B_{ij}$. In a variety of examples that we calculated using B_{ij} as the approximation (for the representative city) the resulting error was typically 5%, and never more than 20%.

The data cover 317 MSA for 16 years, so there are for the four models (four rows) and a total of 4755 transitions (317×15). However, the number of transitions varies by starting rows; and for some receiving cells the number of observations is low or zero. Table 3 reports basic patterns. Diagonal elements form the base (zero) state. For the model of transitions, conditional on starting in state 1, there are positive transitions to all states for computers, so we can obtain three full sets of coefficients (for P^s_{12}, P^s_{13}, P^s_{14}, we have β_{12}, β_{13}, and β_{14}). In particular, for state 4 where there is only one transition, β_{14} coefficients are still identified because β_{14} appears in the denominator of P^s_{12} and P^s_{13}. However, as a practical matter, we are only comfortable reporting results for states where there are a reasonable number of transitions. States with lower numbers of transitions report all insignificant coefficients. We set the minimum number of transitions as 19 for reporting results (although all states with positive transitions are part of the estimating model), and the underlined numbers in Table 3 represent states for which we report results. As one can see, generally we are reporting results for states just off the diagonal, where a city is moving from the current state up or down one.

1.2.1. Covariates

We condition on measures that we view as basically time invariant – either they never change, annual changes are miniscule, or they are recorded

Table 3
Total number of transitions over 15 yr

		To state			
		1	2	3	4
From state	1	2079	198	19	1
	2	149	770	67	1
	3	13	64	944	39
	4	0	1	42	368

Table 4
Logit estimates of conditioned transition probabilities for computers[a]

	Basic specification					Other effects		
	% College educ.	ln(total MSA employ. 1977)	Medium dist.[b] from San Jose	Far from San Jose	Constant	ln(elect. comp. employ. 1977)	HHI (1977)	State corp. rate 1983
From state 1								
P 12 (up)	0.075**	0.904**	– 0.857**	– 0.815**	– 12.5**	0.038	– 2.19	– 0.029
	(0.014)	(0.116)	(0.216)	(0.234)	(1.32)	(0.034)	(4.36)	(0.037)
P 13 (up)	0.168**	1.63**	– 2.20**	– 2.27**	– 23.5**	0.218	– 56.39	– 0.147
	(0.043)	(0.349)	(0.584)	(0.674)	(4.20)	(0.147)	(53.19)	(0.167)
From state 2								
P 21 (down)	– 0.028**	– 0.490**	0.268	0.384	4.03**	– 0.173**	13.2**	0.120**
	(0.019)	(0.103)	(0.254)	(0.279)	(1.19)	(0.044)	(5.78)	(0.046)
P 23 (up)	0.075**	0.590**	– 0.818**	– 0.801**	– 9.86**	0.186**	15.0**	– 0.054
	(0.029)	(0.158)	(0.344)	(0.377)	(1.98)	(0.063)	(6.90)	(0.066)
From state 3								
P 32 (down)	– 0.079**	– 0.282**	0.071	– 0.452	2.23	– 0.084	– 1.58	0.023
	(0.033)	(0.136)	(0.354)	(0.385)	(1.62)	(0.071)	(9.92)	(0.059)
P 34 (up)	0.050	– 0.013	– 0.620	– 0.670	– 3.55*	0.004	– 63.4**	0.058
	(0.032)	(0.159)	(0.416)	(0.422)	(1.96)	(0.105)	(31.6)	(0.091)
From state 4								
P 43 (down)	– 0.193**	– 0.506**	– 0.322	– 0.099	8.23**	– 0.197	– 32.5	0.066
	(0.053)	(0.159)	(0.455)	(0.433)	(2.46)	(0.124)	(26.2)	(0.097)

* Significant at 10% level. Standard errors in parentheses.
** Significant at 5% level.
[a] For state 2 (just past the middle of the distribution) means and standard deviations of % college, ln(*total employ.*), med. distance, far distance, ln(*el. comp. employ*), HHI and state corp. tax are (16.4, 4.70) (11.6, 0.891), (0.189), (0.489), (3.48, 2.71), (0.044, 0.16), and (7.12, 2.37), ln(*el. comp. employ.*) is actually ln(1 + *el. comp. employ.*)
[b] Medium distance is from 1000 to 2250 miles from San Jose. Far is beyond 2250 miles (just beyond Chicago).

infrequently (and are expected to have miniscule annual changes). What covariates are critical to describing a city's environment for computer development? The traditional empirical location literature suggests items such as (1) labor market conditions indicated by wages and, for high-tech industries, availability of high skill workers, (2) access to key national markets, or centers of own industry activity, (3) tax policies, and (4) metro area scale reflecting both local output market size, or local product demand, and scale of local labor market enhancing efficiency in search for particular skill workers (Helsley and Strange, 1991). For computers, Dorfman (1983) suggests access to San Jose and possibly Boston is critical to success for other cities. Proximity enhances upstream and downstream transport supply links within the industry, where for computers a major source of inputs are own industry suppliers. Proximity also may reflect possibilities for inter-city information spillovers from key centers for computers. As with metro area scale and proximity, most of our covariates will have two competing interpretations, which we cannot disentangle with aggregate data. So for metro scale and proximity, there are traditional market interpretations – local product demand and intermediate input transport linkages – and newer externality interpretations – local labor market search and matching processes and inter-city information spillovers.

More recent empirical work suggests other measures. From Glaeser et al. (1992) and Henderson et al. (1995), we expect the nature of the historical industrial environment to play a key role. So, in Henderson et al., a record of high own industry employment in even the 'predecessor' industry (e.g., mainframe computers) raises the probability of having significant new computer employment, as does a history of a diverse industrial environment and related high-tech employment. It is usual to give a static (localization) or dynamic (MAR (Marshall–Allen–Romer)) externality interpretation to own industry scale effects. Here, since we condition on the starting state, we certainly presume some persistence and role for own industry history; but we leave it to Section 2 to directly test for own industry externalities.

Of direct relevance in this section, from this recent empirical literature, a more diverse local industrial environment provides for generalized local information spillovers creating Jacobs-type externalities. In this study we measure diversity by an Hirschman–Herfindahl index based on local industry employment shares. We examine also the impact of employment in related high-tech industries. Besides information spillover interpretations, again, such measures can reflect market considerations. Diversity can measure the richness of inter-industry supply linkages for transport cost minimization (Krugman, 1991) or for economies of scope (Dixit and Stiglitz, 1977) and related high-tech employment can reflect the same. This ambiguity in interpretation also applies to labor market measures where, in addition to enhancing supplies of high skill workers, a better educated work force enhances the quality of local information spillovers, or creates 'knowledge' spillovers as in a Romer (1986)–Lucas (1988) context.

Given these suggestions from the literature and experimentation, we settled on three sets of covariates. For a basic specification we report results on covariates that had consistent robust impacts – percent of adults with college education, metro area scale, and proximity measures. To this basic specification, for the second set we add a state corporate tax measure, the diversity index, and a measure of employment in related high-tech industries, variables with less consistent effects. Finally, we note outcomes from experimenting with other price variables such as wage and local property tax measures.

Table 4 gives the results. We start with the 'basic specification', with four coefficients other than the constant term. Results for four logit models are examined, selecting boxed states in Table 3 for presentation. Starting from state 1, a city can only move up; and, from state 4, only down. Whether one is moving up or down is critical, since expected signs reverse. So we expect an increase in the percent college educated to raise the probability of moving up, but lower it for moving down.

In Table 4, percent college educated and total metro area size (employment) always have the expected signs (except for metro area size for P_{34}), and are generally significant. An increase of one percentage point in college educated increases the probability of moving up by about 16% for P_{13} (i.e., from Eq. (6), the percent increase in the probability level, $\mathrm{d}P/P$, is given approximately by the coefficient 0.1587) or reduces the probability of moving down by about 19% for P_{43}. Education has a standard deviation of 5.3 so a one-standard deviation change in education can almost double the probability of moving up (P_{13}). This represents the benefits for computers of locating in cities with greater supplies of high skill workers, and perhaps a richer information environment. For metro area size, representing both local demand and labor market size effects, the elasticity of the probability is as high as 1.6 for moving up (for P_{13}) and as low as -0.51 for moving down (P_{43}).

In terms of proximity measures, our basic results are for three categories, near (within 1000 miles), medium (1000–2250 miles) or high (over 2250) distance to San Jose. For states 1 and 2, patterns are strong and as expected. Being further from San Jose markedly lowers the chances of moving up and raises the chances of moving down. So for P_{13} being far from San Jose can cause a '220% reduction' in the probability of moving up from state 1 to 3. For higher states, distance effects are mixed and insignificant, indicating for the initial big players mobility is less influenced by distance to San Jose. Distance to Boston or to the thirty Rand McNally national market retail metro centers had no consistent significant effects on transition probabilities. Following the PC revolution, San Jose was 'where its at'.

To try to further quantity the effect of distance to San Jose, we reestimated the model with linear and quadratic distance formulations. As before, results for starting states three and four are insignificant. For P_{13} and P_{23} negative distance effects seemed to be linear throughout. For P_{12} and P_{21} a quadratic formulation suggests that marginal effects drop with distance but stay negative throughout (i.e., they bottom-out at 12,000 miles).

For other covariates we considered a variety of possibilities. The effects of adding on other variables on the coefficients of variables in the basic specification are generally minimal. Measures such as average real annual wages in private sector employment or per person property taxes had no consistent effects and results are not reported. The presumption is that those crude measures do not reflect wages in high-tech sectors and establishment property tax rates (especially given tax holiday competition among locations for high-tech employment). We do report on a second set of three variables. First, employment in associated electronic components (including circuit boards, semi-conductors, and silicon wagers) always raises (lowers) probabilities of moving up (down), but is only significant for the second state model. So whether a city with some small employment in computers fell to the nothing state or rose to the medium state was influenced by the electronic component base. This reflects potentially both down-stream supply connections, and knowledge spillovers flows between the sectors. The second variable concerns state taxes. With one exception in Table 4 (P_{34}) increases in state corporate tax rates lowered (raised) chances of moving up (down), but the effect is only significant for P_{21}.

The last variable considered is the diversity measure HHI for 1977, indicating potential Jacobs-urbanization externalities. HHI is the sum of squares of each of 81 two-digit SIC code industry shares of total local employment (excluding computer employment) – i.e., $\mathrm{HHI}^s = \sum_{k=1}^{81}(\rho_k^s)^2$ where ρ_k^s is the employment in industry k in city s divided by total employment in city s. HHI^s has a maximum value of 1 if all employment in city s is in just one of the 81 industries and a minimum value of 1/81 ($\equiv$ 0.0123) if employment is fully diversified – spread evenly (equal ρ's) over all 81 industries. Lower HHI represent greater diversity which is supposed to be beneficial. Results in Table 4 are at best mixed – in four cases, two significant (P_{21} and P_{24}), there is the expected sign, so a higher HHI with less diversity (as in state 1) lowers chances of getting the industry; but in three cases, one significant (P_{23}), the sign is perverse. The evidence for Jacobs-urbanization externalities (and/or for other market diversity benefits) is much weaker than in Henderson et al. (1995).

In summary, being near San Jose, with a large, well educated labor force greatly enhanced a city's chances of moving up states into more winning categories in the computer high-tech race. A concern might be that these covariates also predict urban growth, so that in fact the probabilities of moving up or down states are really growth driven, not driven by these underlying characteristics. To check on this, we added a covariate of the percent total employment growth in the MSA between 1977 and 1992 to the model. While that variable is often significant and of expected sign, its effect on all significant coefficients of Table 4 variables is negligible.

Table 5
Mean first passage times for hypothetical typical and superior urban sites

Typical						Superior					
		1	2	3	4			1	2	3	4
	1	(1.9)	15	66	218		1	(97)	38	5.6	22
Initial state	2	13	(4.3)	54	208	Initial state	2	234	(32)	4.3)	21
	3	29	20	(5.9)	161		3	282	119	(4.4)	16
	4	45	36	15	(11)		4	303	166	47	(1.3)

Another way of viewing the role of urban characteristics is to examine mean first passage times for different cities based on their heterogeneity. We examine mean first passage times for two hypothetical cities, one for (1) a typical urban site with mean national employment and education level, in the middle from San Jose, and the other for (2) a superior site with employment and education one standard deviation above the mean, near San Jose.[7] Table 5 presents the calculated mean first passage times. The most stark comparison is the mean first passage times to state 4 from below. For a typical site, first times from a lower state to state 4 are 161–218 yr, while for a superior site they are only 16–22 yr. Similarly starting in a higher state, the mean first passage times to the lowest state for a superior site are almost 300 yr versus 13–45 yr for a typical site. Superior sites move up much more quickly and down much more slowly than inferior sites. Correspondingly, on the diagonal, superior sites are quick to first 'revisit' higher states (by either staying there in the first instance or jumping back if they initially exit) and slow to revisit lower states. Heterogeneity of urban areas is critical to location patterns. If not in the highest states, superior sites move there quickly and then only lose ground very slowly.

2. Externalities

In this section we estimate the extent of static and dynamic externalities for computers, quantifying own industry external economies of scale. We also

[7] We did this for two cases. First is for the cell division in Table 4. The problem here is that cells which experience no transitions in Table 3 have no predicted probabilities, so we can only use zeros for those cells. To avoid this problem, we recalibrated the cells to ensure positive transitions everywhere, expanding the first and four cells considerably. We recalculated all numbers in Tables 1 and 4 getting similar results. For both cases, point estimates for transition probabilities for two different transition matrices were calculated based on the logit coefficients, and then corresponding mean first passage times (Eq. (4)) were calculated. For the two cases in terms of cell divisions, qualitative results are very similar and we only report on the first – transition probabilities based on the logit coefficients in Table 4 and zeros for states with no observed transitions in the data.

examine cross-fertilization between computers and electronic components. Estimation of own industry externalities is important for two reasons. First, it tells us whether scale effects could play an important role in persistance in own industry employment patterns. Second, identification of dynamic, or MAR externalities would strongly suggest an information spillover interpretation to own industry scale benefits, as opposed to internal industry market linkage effects (own industry local economies of scope and transport linkages, for intermediate inputs from the own industry). It is hard to imagine why past availability and diversity of suppliers directly affect productivity today, but easier to envision the role of local knowledge stocks (including an historically accumulated information base about local suppliers and linkages) in affecting productivity today.

Prior work in Glaeser et al. (1992) and Henderson et al. (1995) has tried to examine the extent of dynamic externalities, by seeing whether employment growth between two time periods is affected by local historical industrial conditions, such as own industry employment concentrations or industrial diversity in the base period 15–30 yr ago. Urban specialists feel uncomfortable with the notion that industrial conditions from even 15 yr ago really matter, because they observe cities radically shifting employment compositions, breaking patterns of information flows and effects of history. This unease manifests as two formal econometric issues. First, rather than the link between the present and the past representing mostly dynamic externalities, an alternative explanation is that there is a location fixed/random effect in estimation that gives rise to the role of history. The fixed/random effect captures relatively time invariant unmeasured location attributes. For example, differences in unmeasured regional resource endowments persist over time, so current industrial location patterns may be related to historical patterns simply because they draw upon the same relative endowments. Additional time invariant, unmeasured attributes include notions of local culture affecting the local legal, business and institutional climate, as well as attributes of the relatively immobile, specific skill portions of the labor force.

The second econometric issue that most studies are completely silent on (by virtue of their data limitations) concerns the timing, or lag structure to dynamic externalities. What are the effects of industrial environmental conditions from three years ago, five years, ten years ago and so on. Do conditions from even five years ago have any significant effects on industrial productivity today? Even more basic is the question of whether there are dynamic elements to externalities, beyond static agglomeration economies.

This study uses panel data on establishment productivity in computers to identify a lag structure to externalities and to distinguish externalities from contaminating fixed/random effects by first differencing out fixed effects. Identification of dynamic externalities is direct. For a plant, output today directly comes from own inputs today. Controlling for these, if productivity is improved by past external industrial conditions, that is a dynamic externality. Since identification requires first differencing, this introduces big data burdens: year-to-year measurements must be accurate; panels must exist for sufficient periods of time; and there must be sufficient annual variation in the past external industrial environment. Our panels allow us to look for dynamic externalities from seven years before the current year. In terms of annual variation, in our study, past own industry employment varies considerably for urban three-digit industries, changing (absolutely) on average by at least 20% a year (which is comparable to the absolute average annual percentage change in plant inputs of about 30%). That will allow us to identify localization/MAR externalities. For diversity measures such as Hirschman–Herfindahl indices of employment shares, there is too little annual variation to identify externalities in this way (the average absolute change is under 4% a year).

2.1. Econometric model

The data to be used (see below) are panel data on plants. Output of plant i in location j at time t, $y_i(t)$ is hypothesized to have the production relationship

$$\log y_{ij}(t) = \alpha \log \boldsymbol{X}_i(t) + \sum_{l=0}^{m} \beta_l \log \boldsymbol{E}_j(t-l) + \gamma \boldsymbol{N}_{ij} + \delta(t) + f_{ij} + \varepsilon_{ij}(t). \quad (7)$$

$\log \boldsymbol{X}_i(t)$: vector of firm own inputs which are time variant,
$\log \boldsymbol{E}_j(t)$: vector of external industrial environmental variables with a lag structure, going from this year, 0 (static externalities) and then from $l = 1, \dots, m$ for dynamic externalities,
$\boldsymbol{N}_{ij}$: vector of plant/location time invariant variables,
$\delta(t)$: time specific constant term/shock,
f_{ij}: plant and/or location fixed/random effect (e.g., plant age, local institutional environment/culture, regional resource endowments),
$\varepsilon_{ij}(t)$: contemporaneous error term.

Major problems in estimating Eq. (7) are (a) the presence of f_{ij} which affects $\boldsymbol{E}_j(t-l)$ and $\boldsymbol{X}_i(t)$, as well as $y_{ij}(t)$ and (b) the presence of $\varepsilon_{ij}(t)$ which may affect $\boldsymbol{X}_i(t)$ choices and $\boldsymbol{E}_j(t)$, as well as $y_{ij}(t)$.

To deal with fixed effects, we first difference Eq. (7) to get (where, for example, $\Delta\varepsilon_{ij}(t) = \varepsilon_{ij}(t) - \varepsilon_{ij}(t-1)$)

$$\Delta \log y_{ij}(t) = \alpha \Delta \log X_i(t) + \sum_{l=0}^{m} \beta_l \Delta \log \boldsymbol{E}_j(t-l) + \Delta\delta(t) + \Delta\varepsilon_{ij}(t). \quad (8)$$

This eliminates the fixed effect and time invariant firm inputs or locational amenities. For Eq. (8), remaining estimation problems are that (a) the $\Delta \log \boldsymbol{X}_i(t)$ and $\Delta \log \boldsymbol{E}_j(t-l)$ may not be not exogenous to $\Delta\varepsilon_{ij}(t)$ and (b), by construction, $\Delta\varepsilon_{ij}(t)$ and $\Delta\varepsilon_{ij}(t-1)$ are serially correlated within any location (since they share

$\varepsilon_{ij}(t-1)$ in common). To obtain consistent estimates requires the use of instrumental variables, in this case predetermined ones. That is, there is a vector $\boldsymbol{Z}_{ij}(t)$, where $\mathrm{E}[\Delta\varepsilon_{ij}(t), z_{ij}(s)] = 0$, $s = 1,2,\dots,t-2$. Candidates for $\boldsymbol{Z}_{ij}(t)$ include all $\boldsymbol{X}_i(s)$ and $\boldsymbol{E}_j(s)$ for years $s \le t-2$, as well as other predetermined plant or locality conditions. Absent any serial correlation in the $\varepsilon_{ij}(t)$ appropriate instruments are $\boldsymbol{X}_i(s)$ and $\boldsymbol{E}_j(s)$ for $s \le t-2$. Using Hausman tests, we examined exogeneity of the $\boldsymbol{X}_i(t-2)$ and $\boldsymbol{E}_j(t-2)$. Treating the $\boldsymbol{X}_i(t-2)$ as exogenous versus only $\boldsymbol{X}_i(s)$, $s \le t-3$, we could not reject the hypothesis of estimates being the same. However, tests for the $\boldsymbol{E}_j(t-2)$ were less conclusive. So for instruments we use $\boldsymbol{X}_i(s)$, $s \le t-2$, and $\boldsymbol{E}_j(s)$, $s \le t-3$.[8] In general, the length of the instrument list grows as years advance within the sample time frame. In estimation of Eq. (8), each year is treated as a separate equation, with sample size (within year) equal to the number of plants. Cross equation constraints are imposed on all coefficients (except for the intercept, $\Delta\delta(t)$). The number of equation years is the time length of the panel less one year from first differencing. The model is estimated by GMM (Hansen, 1982).[9]

2.2. Data

The sample is the Longitudinal Research Data (LRD) base. We use the 1984–1988 wave of plants (identified in the 1982 Census of Manufacturers), which is treated as a panel in the Annual Survey of Manufacturers. For each plant we have information on real output, labor inputs, and real materials,[10]

[8] Instruments for all years include log level measures for initial historical values – plant age, MSA 1977 total employment, 1982 plant labor, materials and book value. Time varying instruments are appropriately lagged changes in plant inputs after 1982, lagged changes in MSA own and also in other high-tech industry employment back to 1977–1978, and, lagged changes at just $(t-3)$ for total MSA employment (i.e., in the Δ log y_{ij} (1988) equation an instrument is Δ log *MSA employ*$_j$ (85)).

[9] Under conditonal homogeneity, the estimates would be the same as generalized three-stage least squares (Hayashi, 1992), which allow for a variable instrument list by years and account for serial correlation of the $\Delta\varepsilon_{ij}(t)$ across years. In GMM estimation, from the orthogonality conditions on the instruments and error terms, we obtain a criterion function to be minimized. Preliminary parameter estimates are obtained from a variant of 3SLS, used to construct a within year heteroskedastic consistent estimate of the covariance matrix of moments (see also Holtz-Eakin et al. 1988). χ^2 test statistics can be computed both to test the overall model (the over-identifying restrictions in GMM) and for exogeneity of instruments.

[10] Labor is production work hours plus 1800 (h/yr) times non-production workers. Output is total sales value, plus work in progress at year end, less work in progress at year beginning, plus finished product inventories year end, less finished product inventories year beginning, less value of resales. Output is deflated by the producer price series. Materials are (a) costs of materials, parts and contract work, deflated by the general price index for intermediate materials less foods and feeds, (b) costs of fuels deflated by average price per BTU for industrial fuels, and (c) electricity deflated by the average price per KWH for industrial use electricity. All deflators are from the *Statistical Abstract of the USA* published annually by the Census Bureau.

and we can construct a capital stock estimate.[11] For GMM estimates, the panel is balanced requiring plants to remain in the wave throughout and to be in the relevant industry in 1984.

This LRD information on plant inputs and outputs is combined with annual CBP data for each metro area, on employment in the own industry for 1988–1977. We also experimented with industrial environment information for the local county the plant is in, but settled on metro area measures as conceptually most relevant and also, as having dominant effects. There appears to be sufficient numbers of MSAs in the sample to identify effects. On average, there are about two-three plants per MSA in estimating samples (so for non-affiliate computer plants, there are 117 plants and 50 MSAs). We will look at the time varying external environment as consisting of own industry metro employment, local employment in electronic components, and both combined (computers and associated electronic components).

2.3. Estimation and results

In estimation, it became apparent that results differ by type of plant. We have a sample of 'corporate' plants which are plants owned by multi-plant computer firms and a sample of 'non-affiliates', computer plants belonging to firms owning no other computer plants in 1984 (and in 75% of the cases, no other plants in any industry). The idea is that multi-plant computer firms have internal national communications that make them less reliant on the local environment for information flows. In contrast, if firms own only one computer plant, that plant is much more reliant on the local environment for information. So we divide the sample. Non-affiliates average about 40% lower employment than corporate plants, but are still large (average employment in non-affiliate computer plants is 471).

The next consideration is lag structure for external effects. We tested for no dynamic externalities by comparing explanatory power (via a pseudo-F test on the value of the criterion function) for models for non-affiliates with just contemporaneous effects versus contemporaneous plus four prior years. Explanatory power jumped with the latter, indicating dynamic externalities exist. Then we tested for length of lag structure. The basic model is contemporaneous effects plus four prior years – looking back five years ago. Again by pseudo-F tests, adding on two years of lags – looking back seven years ago – did not

[11] Capital stock, K, is based on beginning of year book value (BV) of equipment in 1984, investment, I, in new machinery, a deflator D based on the producer price series for metal working machinery, and $k=0.85$ which is one minus the rate of depreciation. $D=1$ in 1982/1983. Then K (1984) $= BV$ (1984) $\times D$ (1983), K (85) $= k \times K$ (1984) $+ I$ (1984) $\times D$ (1984), K (1986) $= k \times K$ (1985) $+ I$ (1985) $\times D$ (1985), etc.

improve explanatory power for non-affiliate plants in computers and coefficients for those lagged values approach zero. At least within the time horizon of looking back seven years, externality effects do not persist beyond five years ago.

The results are in Table 6. For firm own inputs, coefficients on labor and materials have expected magnitudes, but capital is insignificant, a typical problem in estimation of production functions from this data set. To check that capital stock issues are not driving results we estimated a total factor productivity version of Eq. (8) by GMM as well, obtaining results on externalities that are very similar to those in Table 6.[12] If deflators are accurate, in Table 6, year dummies reflect productivity changes (national productivity growth); but here we suspect they also control for inadequate deflators (with no impact on other coefficients).

Our focus is on the industrial environmental variables. Own industry employment in t and in $t-1$ to $t-4$ for non-affiliates affects contemporaneous productivity. The effects are large.[13] Doubling metro own industry employment today raises output for a plant by 6%, which is thus the magnitude of static own industry (localization) scale effects. Doubling local own industry scale in all of the four prior years raises it by 11% (summing coefficients for $t-1$ to $t-4$), reflecting the magnitude of collective dynamic own industry (MAR) scale effects. Together, a firm operating in a city with consistently double own industry employment compared to another city has 17% greater output than if it operated in the other city. For non-affiliates that is a great reason to cluster into big high-tech centers like San Jose or Austin.

For corporate plants, the story is totally different. The external environment has no positive effects on productivity – in fact, the only significant effects are perverse. Perhaps, IBM does just fine with its high isolated employment in Poughkeepsie, NY.

We also looked for cross over effects. We were unsuccessful in identifying with confidence separate computer and electronic component lag structures to external effects on computers, probably due to multi-collinearity and noise in the data. Combining computers and electronic components into one high tech variable yielded noisy results similar in magnitude to those in Table 6. In the end we just report just what we believe is probably most revelant – a (separate) contemporaneous effect from electronic components. In Table 6, the static scale benefit to computers from electronic component for non-affiliate plants is fairly small but significant.

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[12] Then the LHS variable for year t is growth in output (from $t-1$ to t) minus growth in each input weighted by the plant shares of each factor in output averaged over t and $t-1$ (Hulten and Schwab, 1984). Capital expenditures are a rental rate (0.19) multiplied by current value of capital stock.

[13] For the record, regular fixed effects estimates are very similar. For t to $t-4$ the coefficients on log of own industry employment are, respectively, 0.051, 0.046, 0.011, 0.034 and 0.016.

Table 6
Externality estimates

		Non-affiliates	Corporate
ln(*labor hours*)		0.429**	0.479**
		(0.027)	(0.041)
ln(*materials*)		0.464**	0.365**
		(0.021)	(0.037)
ln(*capital stock*)		– 0.020	– 0.021
		(0.011)	(0.030)
ln(*own indust. employ.*)	t	0.058**	0.0083
		(0.0056)	(0.020)
	$t-1$	0.027**	0.018
		(0.013)	(0.027)
	$t-2$	0.031**	– 0.057**
		(0.0079)	(0.0078)
	$t-3$	0.040**	0.012
		(0.0040)	(0.0031)
	$t-4$	0.015**	– 0.0069**
		(0.0030)	(0.0024)
ln(*electronic components*)	t	0.027**	0.013
		(0.051)	(0.097)
T (yr)		4	4
N (plants)		117	173
Time dummy 1985–1984		– 0.076**	– 0.124**
		(0.0074)	(0.012)
Time dummy 1986–1985		– 0.014**	0.038**
		(0.0046)	(0.0084)
Time dummy 1987–1986		– 0.010	0.0092
		(0.0082)	(0.012)
Time dummy 1988–1987		0.018**	– 0.0088
		(0.0062)	(0.010)

3. Conclusions

In Section 1, we saw that in the 16-year period of computer development, 1977–1992, the basic transition matrix is stationary, with local employment patterns exhibiting no tendency to settle down, nor any tendency of retrenchment during periods of national high-tech employment decline. There is no tendency of relative size distributions of urban computer employment to collapse, go bimodal, or fully spread. Overall computers exhibit some turbulence, with dramatic big winners and losers among cities. In attracting or repelling an industry, urban heterogeneity is important. Large, well educated cities near San Jose have much greater chances of attracting high-tech employment and less of losing it. Finally, we estimated the extent of static and dynamic own industry local externalities, to determine if such externalities could pay a role in persistence of own industry employment patterns and to quantify the impact on productivity of dynamic externalities and the role of local knowledge accumulations. For computers, we found strong evidence of significant dynamic own industry externalities among non-affiliate plants. Corporate plants in computers seem to be self-reliant and not really influenced by externalities.

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