The Review *of* Economics *and* Statistics

GEOGRAPHIC CONCENTRATION AS A DYNAMIC PROCESS

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Abstract—This paper uses data from the Census Bureau's Longitudinal Research Database to describe the dynamics of geographic concentration in U.S. manufacturing industries. Agglomeration results from a combination of the mean reversion and randomness in the growth of state-industry employment. Although industries' agglomeration levels have declined only slightly over the last quarter century, we find a great deal of movement for many geographically concentrated industries. We decompose aggregate concentration changes into portions attributable to plant births, expansions, contractions, and closures. We find that the location choices of new firms play a deagglomerating role, whereas plant closures have tended to reinforce agglomeration.

I. Introduction

FOR a long time economists have noted that industries are often strikingly concentrated in a few states or metropolitan areas.[1] There is no shortage of theories explaining why this concentration may occur (Marshall, 1920; Krugman, 1991b), and in recent years a systematic examination of the facts has begun (Henderson, 1988; Enright, 1990; Krugman, 1991a; Kim, 1995; Ellison & Glaeser, 1997, 1999).

The empirical literature to date has focused on how concentrated various industries are at a point in time, or, in some cases, such as Fuchs (1962) and Kim (1995), at multiple points in time.[2] This paper attempts to add a new dimension to the empirical literature, moving from a static description of geographic concentration to a dynamic one. We disaggregate net changes in concentration levels (or the lack thereof) to examine the decline of old industry centers, the growth of new ones, and industry mobility. Geographic concentration is the outcome of a life cycle process in which new plants are constantly being born, existing plants are expanding and contracting at different rates, and a substantial number of businesses are failing. We explore these dynamic features of U.S. manufacturing concentration over the last 25 years using data from the U.S. Census Bureau's Longitudinal Research Database (LRD).

Analyses of the dynamics of geographic concentration may contribute to a number of often discussed topics. For example, Arthur (1986) and Krugman (1991b) emphasize that, with increasing returns, industry locations today could potentially be the result of historical accidents in the distant past.[3] This creates scope for government action and has implications for understanding such questions as how the industrial structure of Europe may change with integration. One motivation for our study of industry mobility is that it may give a feel for how important historical accidents are in practice and whether Krugman's charming examples are representative. A second active discussion concerns the conditions that favor new business development. One view (associated with Marshall, Arrow, and Romer and sometimes referred to as the MAR model) emphasizes the importance of increasing returns to scale and learning by doing and suggests that firms benefit from being located in industry centers. A second view (associated with Jacobs) argues that the most fertile areas for new plant births are areas with a diverse set of related industries.[4] Various aspects of our dynamic description may enlighten this debate. For example, the Jacobs view suggests that industries may be fairly mobile and that startup activity may be high away from industry centers.

Our work is also motivated by the seeming conflict between the roughly constant level of geographic concentration over the past 130 years (as reported by Kim (1995)) and the dramatic turnover of employment at the plant level documented by Dunne, Roberts, and Samuelson (1989a, 1989b), Davis and Haltiwanger (1992), and others.[5] Is this

[1] Some of the classic studies of the phenomenon are Florence (1948), Hoover (1948), and Fuchs (1962).

[2] Beardsell and Henderson's 1999 study of the computer industry is a noteworthy and interesting exception to this rule.

[3] Holmes (1999), in contrast, emphasizes how industries could be mobile.

[4] See Glaeser et al. (1992) and Henderson, Kuncoro, and Turner (1995) for other empirical evidence on the MAR and Jacobs models.

[5] Those who recall Fuchs (1962) may find our emphasis on stability a bit at odds with his emphasis on the decrease in agglomeration. The index Fuchs uses, however, is problematic in that one would imagine that it will tend to decrease whenever the plant-level concentration of an industry decreases. Fuchs, in fact, notes that decreases in agglomeration were largest in the fastest-growing industries and that slow-growing and shrinking industries on average saw their agglomeration level increase. Kim (1995) reports an increase in agglomeration up to 1947 followed by a

because new plants just tend to be founded across the street from old plants, or do there appear to be forces that maintain equilibrium levels of geographic concentration despite relocation? Among our new observations are that, although levels of geographic concentration are fairly stable, there is a clear decline since the early 1980s. There are also many notable differences between industry groups both in mobility and in the impact of different life cycle events. This part of our analysis raises more questions than it answers, but we hope that it will motivate future research.

We begin in section II by presenting a framework for describing the dynamics of geographic concentration. The section begins with a review of the static framework of Ellison and Glaeser (1997). We then discuss the measurement of industry mobility. Our main observation here is that changes in geographic concentration can be decomposed into decreases attributable to mean reversion in state-industry employment shares and increases attributable to randomness in the process of growth and decline. For geographic concentration to have declined slightly despite randomness in the growth process, we know that there must be mean reversion in state-industry growth. The interesting unknowns are how rapid the declines of industry centers are and how much random growth bolsters concentration. Subsequently, we discuss the further decomposition of agglomeration changes into components that are attributable to events at various stages of the plant life cycle: new firm startups, the opening of new plants by existing firms, the growth and decline of existing plants, and plant closures. Whether each of these stages tend to reinforce or dissipate concentration is again an empirical question.

After describing the LRD data in section III, we describe the patterns we find in sections IV and V. Section IV contains our results on industry mobility. Our most basic observation is that industries are fairly mobile. By itself this seems like an important piece of evidence in support of the idea that observed industry concentration levels are determined by equilibrium forces.[6] The mobility patterns do not suggest a great role for historical accidents and are more supportive of the Jacobs view than they are of the MAR view. Richer patterns appear in examining different subsets of industries. The textile industries, for example, are a noteworthy exception to the general pattern and exhibit little mobility.

Section V contains our results on geographic concentration and the plant life cycle. One of the more striking findings of this section is that, although new plant births are higher in areas where an industry is concentrated, the increase is substantially less than one for one. In fact, new plant births are sufficiently dispersed so as to act on average

to reduce geographic concentration. Although the lack of concentration of new plant births in old industry centers is somewhat supportive of the Jacobs view, the deagglomerating role that births play does not support a model in which concentration is maintained by clusters of new firm births. The expansion and contraction of existing plants also on net acts to reduce agglomeration. The one life cycle stage that acts to maintain agglomeration is the plant closure process: plants in industry centers are less likely to close. Existing theories again do not seem to capture this well. We again look in detail at various industry groups and at different time periods.

II.   A Framework for the Dynamics Geographic Concentration

In this section, we briefly discuss Ellison and Glaeser's (1997) index of geographic concentration and then introduce two decompositions of concentration changes. The first of these focuses on industry mobility, and the second focuses on events at various stages of the plant life cycle.

A.   Background: The EG Concentration Index and Some Facts

The Ellison and Glaeser (hereafter, EG) index of the degree to which industry i is geographically concentrated at time t is given by

$$\gamma_{it} \equiv \frac{G_{it}/(1 - \Sigma_s s_{st}^2) - H_{it}}{1 - H_{it}},$$

where

s_{ist} is the share of industry i's time t employment located in state s,

$G_{it} \equiv \Sigma_s (s_{ist} - s_{st})^2$ is a sum of squared deviations of the industry's state employment shares s_{ist} from a measure, s_{st}, of the states' shares of employment in the average industry, and

H_{it} is a Herfindahl-style measure of the plant-level concentration of employment in an industry: $H_{it} \equiv \Sigma_k e_{ikt}^2/(\Sigma_k e_{ikt})^2$ where e_{ikt} is the level of employment in the kth plant in industry i at time t.[7]

The motivation for the EG index is that it is an unbiased estimate of a sum of two parameters that reflect the strength of spillovers and unmeasured comparative advantage in a benchmark model. Under particular assumptions, the index is independent of the number and size of plants in the

decrease from 1947 to 1987, with the largest part of the decrease occurring between 1947 and 1967.

⁶ Other key pieces of evidence supporting this view are Kim's 1995 finding that 1860 and 1987 agglomeration levels are highly correlated and Maurel and Sedillot's 1999 finding of correlation between levels of agglomeration in the United States and in France.

⁷ In a slight departure from Ellison and Glaeser (1997), the measure s_{st} we use here is the unweighted arithmetic mean of the s_{ist} across the industries in our sample; that is, $s_{st} = (1/I) \Sigma_i s_{ist}$ where I is the total number of industries. The use of the unweighted mean facilitates the development of an unweighted decomposition, which we feel provides a more informative reflection of the dynamics of concentration in a typical industry.

industry and of the geographic divisions used to form the measure.

In practice, changes in the value of the EG index over time are well approximated by changes in the difference between G_{it} and H_{it}. Ellison and Glaeser (1997) refer to G_{it} as the raw geographic concentration of employment in an industry. The subtraction of H_{it} is a correction that accounts for the fact that the G_{it} measure would be expected to be larger in industries consisting of fewer larger plants if locations were chosen completely at random. Because plant size distributions tend to change fairly slowly, the correction is less important in cross-time comparisons within a short time period than in cross-industry comparisons.

Before proceeding with the development of our measurement framework, it will be useful to have seen a few facts. The first row of table 1 reports the mean across U.S. three-digit manufacturing industries of the EG index (as computed from data on employment at the state level.) The overall pattern is that concentration of the mean industry remained fairly constant between 1972 and 1982, and then fell by approximately 10% in the following decade.

The second and third rows of table 1 give the means of G_{it} and H_{it} from 1972 to 1992. These show that the decline in the EG index is associated mainly with a decrease in raw geographic concentration. Although there is no clear trend, the average plant-level Herfindahl is slightly higher in 1997 than in 1972. Hence, the decline in the EG index is slightly larger than the decline in raw concentration. Table 2 illustrates a second important fact: the substantial differences that exist in concentration across industries change little over time. The correlation of EG indices measured five years apart is approximately 0.97, and the correlation between the 1972 and 1992 values is 0.92. Thus, the ongoing dynamic process somehow manages to maintain fairly stable levels of agglomeration. This stability is even more striking in Kim's 1995 calculation of Hoover's coefficient of regional localization for two-digit industries. The correlation between the 1860 and 1987 values of the localization coefficients he reports is 0.64.

B. Geographic Concentration and Industry Mobility

The combination of turnover at the plant level and stability in agglomeration levels is compatible with a wide range of mobility patterns between two extremes: agglomeration could be constant because new plants just replace

old plants at the same location, so state-industry employments do not change; or, alternatively, some equilibrating forces may keep agglomeration roughly constant even while the industries' locations are changing greatly. Here, we develop a simple framework for thinking about how changes in agglomeration will result from a combination of the systematic growth and contraction of old industry centers and randomness in growth rates.

Consider the following simple regression in which we treat the change in state-industry employment shares (for example, the share of industry i's employment located in state s) as a function of the growth of the state's average employment share (that is, the average across industries of the share of employment in state s) and the difference between initial state-industry share and the state's average employment share:

$$s_{ist+1} - s_{ist}$$
$$= \hat{\alpha} + \hat{\beta}(s_{ist} - s_{st}) + \hat{\gamma}(s_{st+1} - s_{st}) + \hat{\epsilon}_{ist}, \qquad (1)$$

where

s_{ist} is the share of industry i's employment in state s as of time t,

s_{st} is the average of this variable for state s across industries,

$\hat{\alpha}$, $\hat{\beta}$, and $\hat{\gamma}$ are estimated coefficients, and

$\hat{\epsilon}_{ist}$ is an estimated error term which is, by construction, orthogonal to each of the regressors.

Note that this regression is specified so that each of the variables have mean zero and so that the two regressors are orthogonal. As a result, the OLS estimates will always be that $\hat{\alpha} = 0$ and $\hat{\gamma} = 1$.

In this section, we will analyze changes in agglomeration levels using the raw concentration component, G_{it}, of the EG index of concentration.[8] Write $G_t \equiv (1/I) \sum_i G_{it}$ for the

TABLE 2.—CORRELATION OF ELLISON-GLAESER INDEX OVER TIME (1972–1992)

	1972	1977	1982	1987
1977	0.973			
1982	0.967	0.973		
1987	0.918	0.924	0.969	
1992	0.917	0.925	0.962	0.975

The table gives the correlation between the values of the EG index when computed using data from different years.

TABLE 1.—MEAN LEVELS OF GEOGRAPHIC CONCENTRATION 1972–1992

	1972	1977	1982	1987	1992
Ellison-Glaeser index (γ)	0.039	0.039	0.038	0.036	0.034
Raw concentration (G)	0.049	0.049	0.049	0.046	0.045
Plant Herfindahl (H)	0.013	0.012	0.012	0.012	0.013
Employment weighted mean γ	0.038	0.038	0.037	0.035	0.034

The table reports means (across 134 U.S. three-digit manufacturing industries) of the Ellison-Glaeser index of geographic concentration and two components: the simpler raw geographic concentration measure and a Herfindahl measure of plant-level concentration.

[8] As we noted previously, the trends in raw concentration and in the EG index are fairly similar. Focusing on raw concentration rather than on the EG index allows us to bring out the main observations of this section more simply. We will discuss a more complex decomposition that also accounts for changes in plant-level concentration in the next subsection.

mean of this variable across industries. Simple algebra reveals that

$$
\begin{aligned}
G_{t+1} - G_t &= \frac{1}{I} \left[\sum_{is} (s_{ist+1} - s_{st+1})^2 - \sum_{is} (s_{ist} - s_{st})^2 \right] \\
&= \frac{1}{I} \left[\sum_{is} ((1 + \hat{\beta})s_{ist} - \hat{\beta}s_{st} + \hat{\gamma}(s_{st+1} - s_{st}) \right. \\
&\quad \left. + \hat{\epsilon}_{ist} - s_{st+1})^2 - \sum_{is} (s_{ist} - s_{st})^2 \right] \\
&= \frac{1}{I} \left[(2\hat{\beta} + \hat{\beta}^2) \sum_{is} (s_{ist} - s_{st})^2 + \sum_{is} \hat{\epsilon}_{ist}^2 \right] \\
&= (2\hat{\beta} + \hat{\beta}^2)G_t + \frac{1}{I} \sum_{is} \hat{\epsilon}_{ist}^2.
\end{aligned}
$$

This equation decomposes changes in concentration into the sum of two terms, which we will describe as the effects of *mean reversion* and of *randomness* (or dispersion) in the local employment process. The first term in the decomposition, $(2\hat{\beta} + \hat{\beta}^2)G_t$, depends on the extent to which net change in employment is correlated with the initial gap between the state-industry employment share and the state's share of employment in the average industry. When β is negative, current centers of the industry are declining in importance and/or employment is tending to increase in areas that initially have a below-average share of employment in the industry. In this case, we will describe the state-industry employment levels as displaying mean reversion, and the first term in the decomposition is the decrease in agglomeration that is attributable to this tendency. Conversely, when β is positive and industry centers are growing, the first term reflects a consequent increase in agglomeration.

The second term in the decomposition, $\sum_{is} \hat{\epsilon}_{ist}^2$, captures the effect of randomness in the growth (and decline) in state-industry employments. The magnitude of this component reflects the degree of heterogeneity in the experience of states that initially have similar concentrations of employment in a given industry. For example, it will be larger if some industry centers take off while others fail, and if some areas where the industry is not present are very successful in attracting new plants while others are not. This term is always positive: randomness of the growth process can always be thought of as increasing agglomeration levels. For the overall level of agglomeration in U.S. manufacturing to have declined slightly over the last twenty years, it must be that $\hat{\beta}$ is negative so that the agglomerating effect of random shocks has been counterbalanced by systematic mean reversion.

The role of mean reversion of state-industry employment and random shocks in maintaining a steady level of concentration over time is analogous to the classic discussion in statistics courses of the fact that, for the distribution of people's heights to remain roughly the same over time, it must be the case that children of tall parents are on average shorter than their parents and children of short parents are on average taller than their parents.

C. Geographic Concentration and the Plant Life Cycle

A new geographic center of activity in an industry can develop in a number of different ways: the area can be a hotbed for startup firms, it may succeed in attracting the new plant investments of existing firms, or a core of preexisting firms may grow into a position of prominence. In this subsection, we describe a decomposition of changes in agglomeration into portions due to various life cycle events.

Suppose that the data allow the employment change in a state-industry to be partitioned into portions attributable to one of J categories of events (such as to new plant births, plant closures, and so on):

$$
E_{ist+1} - E_{ist} = \sum_j \Delta E_{ist}^j,
$$

where E_{ist} is the employment level of industry i in state s at time t, and ΔE_{ist}^j is the change in employment due to events of type j. Denote by ΔE_{it}^j the aggregate amount of employment change due to the jth growth process.

In the previous subsection, we focused on a simple raw concentration measure of geographic concentration. We justified this by noting that it is an empirical fact that the overall distribution of plant sizes has not changed as much over the last twenty years. Such an argument, however, cannot justify ignoring changes in plant Herfindahls when decomposing concentration changes into portions attributable to various life cycle stages. Although the overall plant-level concentration of industries has remained roughly constant (using the plant Herfindahl measure), new firm births clearly tend to reduce this concentration and plant closures tend to increase it. Hence, the effect of births or closures on raw concentration and on the EG index may be quite different.

To obtain a tractable decomposition, we focus on a measure of agglomeration, $\tilde{\gamma}$, which closely approximates the EG index:

$$
\tilde{\gamma}_{it} \equiv \frac{G_{it}}{1 - \sum_s s_{st}^2} - H_{it}.
$$

(The approximation involves ignoring the $1 - H_{it}$ denominator of the EG index.[9]) Writing $G_t \equiv \frac{1}{I} \sum_{it} G_{it}$ for the average raw concentration across industries, we first define in equation (3) a decomposition of the aggregate change in

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[9] Ignoring changes in the denominator makes decomposing concentration changes straightforward. The changes in H attributable to the various stages of the life cycle typically have a magnitude of approximately 0.001. Hence, ignoring the denominator will not change in a meaningful way our description of the effects of the various life cycle changes.

raw concentration into portions attributable to events in each of the J categories; that is, we define measures ΔG_t^j such that $G_{t+1} - G_t = \sum_{j=1}^{J} \Delta G_t^j$. Next, in equation (4), we define a similar decomposition of changes in the average plant Herfindahl: $H_{t+1} - H_t = \sum_{j=1}^{J} \Delta H_t^j$. Our final measure of the portion of the change in the index $\bar{\gamma}_t \equiv \frac{1}{I} \sum_i \bar{\gamma}_{it}$ attributable to the jth stage of the life cycle is then just

$$\Delta \tilde{\gamma}_t^j \equiv \frac{\Delta G_t^j}{1 - \sum_s s_{st}^2} - \Delta H_t^{j}.^{10}$$

To decompose raw concentration changes, we first define a measure, Δs_{ist}^j, of the portion of the change in state s's share of employment in industry i that is due to the jth growth process by

$$\Delta s_{ist}^j \equiv \frac{\Delta E_{ist}^j - s_{ist}\Delta E_{it}^j}{E_{it+1}}.$$

The numerator of the right-hand-side contains a difference of two terms: the actual employment change due to the events of the jth type and the employment change that would have resulted if events of the jth type had occurred in proportion to initial state-industry employment. The denominator is end-of-period industry employment. If, for example, new firm births in an industry occurred proportionally to the initial state-industry employments (and there were no differences in the size of new firms across states), then there would be no changes in state-industry employment shares caused by new firm births, and $\Delta s_{ist}^{\text{new birth}}$ would be zero for each state. Because state-industry shares change nonlinearly with changes in each plant's employment, our partition of share changes into portions attributable to each of several factors is by necessity arbitrary. We believe, however, that this definition seems natural, and it satisfies the crucial adding-up constraint: $s_{ist+1} - s_{ist} = \sum_j \Delta s_{ist}^j$.

We then estimate for each of the J categories of employment changes a growth regression of the form

$$\Delta s_{ist}^j = \hat{\alpha}_j + \hat{\beta}_j(s_{ist} - s_{st}) + \hat{\gamma}_j(s_{st+1} - s_{st}) + \hat{\epsilon}_{ist}^j. \quad (2)$$

The estimates from these regressions will satisfy $\sum_j \hat{\beta}_j = \hat{\beta}$, $\sum_j \hat{\gamma}_j = \hat{\gamma}$ and $\hat{\epsilon}_{ist} = \sum_j \hat{\epsilon}_{ist}^j$, where $\hat{\beta}$, $\hat{\gamma}$, and $\hat{\epsilon}_{ist}$ are the estimates from the employment change regression (1) of the

previous section. The aggregate change in raw concentration is related to the parameters of these regressions by

$$G_{t+1} - G_t = (2 + \hat{\beta})\hat{\beta}G_t + \frac{1}{I} \sum_{is} \hat{\epsilon}_{ist}^2$$

$$= \sum_j \left(\hat{\beta}_j(2 + \hat{\beta})G_t + \frac{1}{I} \sum_{is} \hat{\epsilon}_{ist}\hat{\epsilon}_{ist}^j \right)$$

$$= \sum_j \Delta G_t^j,$$

where the change in raw concentration due to events in the jth category is defined by

$$\Delta G_t^j \equiv \left(\hat{\beta}_j(2 + \hat{\beta})G_t + \frac{1}{I} \sum_{is} \hat{\epsilon}_{ist}\hat{\epsilon}_{ist}^j \right). \quad (3)$$

As motivation for this definition, note that ΔG_t^j is a sum of four terms:

$$\Delta G_t^j = (2\hat{\beta}_j + \hat{\beta}_j^2)G_t + \frac{1}{I} \sum_{is} \hat{\epsilon}_{ist}^{j2} + \hat{\beta}_j \sum_{k \neq j} \hat{\beta}_k G_t$$

$$+ \frac{1}{I} \sum_{is} \hat{\epsilon}_{ist}^j \sum_{k \neq j} \hat{\epsilon}_{ist}^k.$$

The first two terms reflect the change in concentration due to the mean reversion and randomness in employment changes of type j. The third and fourth terms are what we thought was a natural allocation of the additional agglomeration changes that result from correlations between employment changes due to events of type j and due to events of other types.

The decomposition of changes in the plant Herfindahl index into portions due to events at each stage of the life cycle is analogous with plant-industry employments taking the role of state-industry employments. Let e_{ikt} be the employment level in the kth plant in industry i at time t. We write $z_{ikt} \equiv e_{ikt}/\sum_k e_{ikt}$ for plant k's employment share within its industry. Our plant Herfindahl measure for industry i can be written as $H_{it} = \sum_k z_{ikt}^2$. We write $H_t = \frac{1}{I} \sum_i H_{it}$ for the average of this measure across industries. We write $\Delta z_{ikt} \equiv z_{ikt+1} - z_{ikt}$ for the change in plant k's employment share, with the convention that z_{ikt} is set to zero if plant k is not in industry i at time t. (For example, $\Delta z_{ikt} = -z_{ikt}$ if the kth plant in industry i has switched to another industry at time $t + 1$.)

Assume again that we have a partition of employment changes in each plant-industry into portions attributable to events in each of J categories:

$$\Delta e_{ikt} = \sum_j \Delta e_{ikt}^j.$$

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[10] Note that our definition of $\Delta\tilde{\gamma}^j$ ignores the effect on measured concentration of changes in the denominator $1 - \sum_s s_{st}^2$. For this reason, although our decompositions satisfy $G_{t+1} - G_t = \sum_{j=1}^{J} \Delta G_t^j$ and $H_{t+1} - H_t = \sum_{j=1}^{J} \Delta H_t^j$, the sum of the $\Delta\tilde{\gamma}^j$ will not be exactly equal to $\tilde{\gamma}_{t+1} - \tilde{\gamma}_t$. The difference will be small if changes in $\sum_s s_{st}^2$ are small, that is, if the distribution of state sizes does not change much over each five-year period. It would be tedious, but not difficult, to derive a decomposition of $\Delta\tilde{\gamma}_t$ that does add up exactly. The difference between $\Delta\tilde{\gamma}_t$ and $\sum_j \Delta\tilde{\gamma}_t^j$ as we've defined it is equal to $G_{t+1} (\sum_s s_{st+1}^2 - \sum_s s_{st}^2)/((1 - \sum_s s_{st}^2)(1 - \sum_s s_{st+1}^2))$. This term could be decomposed into portions attributable to each of the J life cycle stages in a manner analogous to our decomposition of changes in the plant Herfindahl.

As before, we define the portion of the change in each plant's share of employment to events in each category by

$$\Delta z^j_{ikt} = \frac{\Delta e^j_{ikt} - z_{ikt}\Delta E^j_{it}}{E_{it+1}}.$$

This definition again yields an allocation of share changes across the categories; that is, $z_{ikt+1} - z_{ikt} = \sum_j \Delta z^j_{ikt}$. We then estimate separate employment change regressions for each of the J components of changes in the plant-industry employment shares,

$$\Delta z^j_{ikt} = \hat{\alpha}_j + \hat{\beta}_j \tilde{z}_{ikt} + \hat{\epsilon}^j_{ikt},$$

where $\tilde{z}_{ikt} \equiv z_{ikt} - \dfrac{1}{N_i}$ for N_i, the number of plants that operate in the industry either in period t or in period $t + 1$.

We show in the appendix that the definition analogous to our definition of ΔG^j_t,

$$\Delta H^j_t \equiv (2\hat{\beta}_j + \hat{\beta}_j\hat{\beta})\left(H_t - \frac{1}{I}\sum_i \frac{1}{N_i}\right) + \frac{1}{I}\sum_{ik}\hat{\epsilon}^{j2}_{ikt}$$

$$+ \frac{1}{I}\sum_{ik}\hat{\epsilon}^j_{ikt}\left(\sum_{l\neq j}\hat{\epsilon}^l_{ikt}\right), \tag{4}$$

again provides a decomposition that satisfies

$$H_{t+1} - H_t = \sum_j \Delta H^j_t.$$

III. Data

The main data used in this paper come from the U.S. Census Bureau's Longitudinal Research Database. The LRD is a longitudinal microdata file that links the information obtained from the manufacturing establishments included in the quinquennial Census of Manufacturers (since 1963) and the Annual Survey of Manufactures (since 1972). McGuckin and Pascoe (1988) and Davis, Haltiwanger, and Schuh (1996) provide a detailed account of the information found in this data set. In this study, we focus the analysis on the five census years since 1972 (1972, 1977, 1982, 1987, and 1992), using 1972 as a base year. This provides between 312,000 and 370,000 observations in every census year, covering every manufacturing establishment in the United States. We will briefly address some of the major features of this data set here.

One of the advantages of the LRD is that it makes it possible to follow a plant through the stages of its life cycle. Our analysis will focus on a breakdown of employment changes into five categories: births of new firms, the opening of new plants by existing firms, the expansion or contraction of existing plants, plant closures, and switches of plants between industries. We define a plant birth between time t and time $t + 1$ as a plant that appears in the time $t + 1$ census and either does not appear in the time t

census or does so with zero reported employment. We obtain our first two categories of employment change by classifying the birth of an establishment that is not part of a firm owning other establishments covered by the Census of Manufactures as a "new firm birth," and the birth of an establishment that is owned by a firm that had establishments in previous censuses as an "old firm birth."[11] Using this distinction, an average of 87% of all newly created plants in our four five-year intervals can be classified as new firm births. These plants are smaller on average than the plants opened by existing firms and account for approximately 50% of employment growth due to plant births. Our third category of employment change is the net expansion and contraction of plants that had positive employment in the industry at time t and that are still in operation with strictly positive employment at time $t + 1$. Our fourth category, plant closures, consists of all changes attributable to plants that had positive employment in the industry at time t and have zero employment or do not appear in the time $t + 1$ census. Finally, to make the employment changes add up to the total employment change, we need a fifth category: switches. This category includes all employment losses or gains in an industry that are attributable to plants that were classified as belonging to the industry at time t being classified as belonging to another industry at $t + 1$ and vice versa.[12] Although some of these switches undoubtedly reflect real changes in the activity of plants, others are likely just reclassifications, thus, we will only briefly discuss results on switches.[13]

We measure the level of economic activity in an industry in a given area by total employment in all manufacturing establishments excluding auxiliary units. We use the fifty U.S. states plus the District of Columbia as our geographic units. At the industry level, we examine 134 manufacturing industries corresponding to three-digit industries in the 1987 Standard Industrial Classification (SIC).[14]

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[11] These new firm births could be connected to firms that existed in the previous census year but did not have a presence in manufacturing. We believe, however, that a large majority of these plants represent true entrepreneurship and the formation of a new firm, not just a new plant.

[12] There is some arbitrariness in how one allocates the growth of plants that both change employment and switch industries. The convention we have adopted is to assign the full net expansion to the initial industry. For example, if a plant is listed as having one hundred employees in industry A at time t and eighty employees in industry B at time $t + 1$, we regard industry A as having lost twenty employees in a contraction and eighty in a switch and industry B as having gained eighty employees in a switch.

[13] See McGuckin and Peck (1992).

[14] The sample consists of all manufacturing industries except SICs 211, 212, 213, 214, 237, and 381. The first five of these were omitted because there were large employment changes attributable to plants being reported as having shifted between the industry in question and a closely related industry, for example, between the fur industry and the women's outerwear industry. We felt that these switches may well have been reclassifications rather than real changes, and, because the industries in question were also fairly agglomerated, we worried that they could have a large effect on our results. The search and navigation equipment industry (381) was excluded because of a major discontinuity in employments over time, which might be due to recoding in the years prior to 1987 to make them consistent with the 1987 SIC.

TABLE 3.—PATTERN OF RAW CONCENTRATION CHANGES ACROSS INDUSTRIES

Set of Industries [Number of Industries in Brackets]	Mean γ (1972)	Average Correlation between 1972 and 1992 State Shares	Estimates		Average Five-year Percentage Change in Raw Concentration		
			β	σ	Total	Mean Reversion	Dispersion
Full sample [134]	0.039	0.86	−0.062	0.010	−2.4	−12.0	9.6
Geographically concentrated [45]	0.088	0.88	−0.043	0.010	−2.5	−8.4	5.9
Geographically unconcentrated [45]	0.006	0.86	−0.116	0.008	−0.1	−21.7	21.5
Concentrated high technology [6]	0.103	0.82	−0.065	0.013	−4.8	−11.9	7.0
Concentrated natural resource [11]	0.052	0.90	−0.059	0.007	−5.7	−11.1	5.4
Concentrated textile & apparel [14]	0.111	0.88	−0.015	0.010	2.1	−2.8	4.8
Concentrated crafts [6]	0.048	0.79	−0.064	0.011	−1.6	−12.2	10.7

The table reports a number of statistics relating to industry mobility. The first column gives mean EG index for the set of industries in 1972. The second reports the average correlation between each state's share of the industry's employment in 1972 and 1992. The third and fourth columns present a coefficient estimate and the estimated residual standard deviation from regression (1). The final three columns report the average percentage change in raw geographic concentration attributed to mean reversion and dispersion as described in subsection IIB.

Obviously, many other choices were possible. In industrial organization, a three-digit industry definition is usually regarded as too broad. We agree wholeheartedly in the context of defining industries to study product market competition. For example, the four-digit classification divides the three-digit men's clothing industry (SIC 323) into subcategories such as men's shirts, underwear, neckties, trousers, and work clothes. A consumer who wants a shirt is clearly unlikely to buy a pair of underwear instead. The four-digit industries are less distinct, however, on the production technology side. The same plant may produce products in several four-digit industries, and it is not uncommon to see plants coded as belonging to different industries in different censuses. Changes due to plants switching industries are very large in a decomposition of changes in the concentration of four-digit industries. It is less common to see plants codes as switching between three-digit industries, and we felt that decompositions based on the three-digit definition provided a clearer picture. Ellison and Glaeser (1997) note that in 1987 the mean EG index is similar when measured using three- or four-digit industries (the means are 0.045 and 0.051, respectively) and discuss the extent to which the four-digit subindustries of three-digit industries are coagglomerated.

The choice of the geographic unit is more arbitrary. Some agglomerations are very tight and some involve plants spread over a large area. A state-based measure would have failed to identify, for example, the classic agglomeration of glove-making firms around Gloversville, New York, in the late nineteenth and early twentieth century. A county- or MSA-based measure would not reveal the full extent of the agglomeration of pharmaceutical firms in New Jersey or of automobile manufacturers in Michigan. Ellison and Glaeser (1997) describe the frequency with which agglomerations seem to be a county, state, and regional phenomenon. Our focus on state-level agglomeration makes our results comparable to the largest part of the evidence in Ellison and Glaeser (1997).

IV. Geographic Concentration and the Movement of U.S. Manufacturing Industries: 1972–1992

As we noted earlier, the stability of geographic concentration is consistent with two very different mobility patterns: agglomeration could be constant because new plants just replace old plants at the same location, or, alternatively, some equilibrating forces may keep agglomeration roughly constant even while the industry's locations are changing greatly. Arthur (1986) and Krugman (1991b) emphasize the potential for locations to be locked in by historical accidents with all the accompanying possibilities for inefficiency. Holmes (1999) notes that MAR externalities can also be compatible with industry mobility.

Table 3 contains parameter estimates for the state-industry employment change regression (1) for different subsamples of industries. Observations from all four periods have been pooled in each subsample. The first column gives the average EG index of each subgroup. The second gives the correlation between each state's shares of each industry's employment in 1972 and 1992. Note that these are quite high, although not as high as the 0.92 correlation between 1972 and 1992 values of the EG index. For the entire sample, the estimated coefficient β on the departure of the state-industry employment share from the average employment share is −0.063. Hence, over the twenty-year period, states in which an industry is initially overrepresented in an area would be expected to experience a decline in its excess employment of nearly one-fourth.

The sixth and seventh columns of the table present our decomposition of how much of the change in concentration is attributable to mean reversion and to dispersion in the employment change process. In the full sample, the mean reversion effect is sufficiently strong so as to produce a 12% decrease in agglomeration every five years, while the dispersion effect by itself would lead to a 9.6% increase. The effects almost balance each other and result in the net negative of −2.4%. The magnitudes of the two separate effects indicate that there is a substantial degree of industry mobility relative to the degree to which concentration levels have changed. This view contrasts with the emphasis of

some previous authors (Krugman, 1991a) on historical accident.

There are clear differences in the employment change patterns in different groups of industries. In the high-concentration subsample (which contains the most-agglomerated third of industries according to the 1972 EG index), we estimate a β that is smaller than that of the overall sample. Perhaps surprisingly, there seems to be no more or less randomness in the growth process of this subsample (as measured by $\hat{\sigma}$) than in the full sample. The low-concentration subsample (which contains the least-concentrated third of the industries in the sample) is distinguished by having much stronger mean reversion; the estimated β of -0.116 indicates that, on average, areas in which an industry was overrepresented saw their excess employment reduced by approximately 40% over the twenty-year period.

The final four lines of the table are concerned with the behavior of four sets of industries with moderate to high concentration. Three of the four groups display about as much mean reversion as the average industry (geographically concentrated or not). We constructed these samples manually in an attempt to categorize the industries that appeared at the top of our concentration list. The four samples include the majority of the industries in our "geographically concentrated" sample (as well as some others that are only slightly less concentrated). The one subsample which is very different is the set of textile industries (consisting of industries within SIC groups 22 and 23 for which the 1972 EG index was in the top sixty). In these industries, there is much less mean reversion than in the other concentrated industries, and the degree of concentration has risen over time. In each of the other subsamples, raw concentration levels have declined. The behavior of the high-technology subsample is fairly similar to the full sample with the one noteworthy feature being that there is a larger random component in the employment changes.[15] (This randomness, however, is not sufficiently large so as to sustain the high initial level of agglomeration.) The set of industries for which we imagined natural resources may be relevant to agglomeration (including several food, lumber, paper, petroleum and primary metals industries) appears to have substantially less randomness in the growth and decline of state-industries.[16] The pattern in the craft industries is quite similar to the pattern in the full sample.[17]

Table 4 reports separate decompositions of the decline in raw concentration into components stemming from mean reversion and from dispersion for each of the four five-year intervals in our sample. In all four periods, concentration declines, but the change has been most pronounced since 1982. The dispersion effect has been larger in the second

TABLE 4.—RAW CONCENTRATION CHANGES AND INDUSTRY
MOVEMENT OVER TIME

| Time Period | Percentage Change in Raw Concentration | | |
	Total	Mean Reversion	Dispersion
1972–1977	−1.3	−9.6	8.3
1977–1982	−1.4	−10.3	8.9
1982–1987	−4.3	−16.6	12.3
1987–1992	−2.7	−11.7	9.0

The table presents the decomposition of changes in raw concentration described in subsection IIB for four separate periods.

half of the period than it was in the first, and thus the more rapid decline in agglomeration that has taken place in the last half of the period can be more than completely attributed to an increase in the rate at which old industry centers have tended to decline.

Overall, the most important lesson is that (outside of textiles) many concentrated industries are quite mobile. The fact that concentration does not simply take the form of industries never moving is strong evidence that levels of geographic concentration are an equilibrium phenomenon whether due to increasing returns or cost differences. Mobility is not incompatible with Jacobs or MAR externalities but would lead us to downplay the importance of distant historical accidents for many concentrated industries.

V. Agglomeration and the Plant Life Cycle

In this section, we discuss how events at various stages of the plant life cycle have contributed to the geographic concentration of U.S. manufacturing industries. One motivation for this exercise is the basic desire to understand where in the life cycle concentration arises, how the dynamics of concentrated and unconcentrated industries differ, and why geographic concentration has begun to decline in the last decade. Another is the desire to explore the contrast between the MAR emphasis on within-industry spillovers and the Jacobs emphasis on diverse environments creating hotbeds for startup activity.

Our analysis of data from the LRD focuses on a description of employment changes as resulting from five categories of events: births of new firms, openings of new plants by existing firms, the growth or decline in employment at existing plants that continue to operate in the industry, plant closures, and switches of plants from one industry to another. Somewhat surprisingly, we will see that new firm births and expansions of existing plants have a deagglomerating effect whereas the plant closure process tends to reinforce concentration levels.

A. Overall Patterns

Table 5 lists the coefficient estimates from regressing each component of employment change, Δs^j_{ist}, on the initial excess concentration of the industry in the state, $s_{ist} - s_{st}$, and on the overall growth of the state, $s_{st+1} - s_{st}$ as in

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[15] The concentrated high-technology sample consists of SICs 357, 365, 372, 376, 385, and 386.

[16] The concentrated natural resource sample consists of SICs 203, 207, 241, 242, 243, 261, 262, 291, 331, and 332.

[17] The concentrated crafts sample consists of industries 326, 328, 387, 391, 393, and 396.

TABLE 5.—EMPLOYMENT CHANGES AT VARIOUS LIFE CYCLE STAGES

Independent Variable	Dependent Variables: Components of Employment Share Changes, Δs^j_{ist}					
	Total Change	New Firm Births	Old Firm Births	Closures	Expansions/Contractions	Switches
$s_{ist} - s_{st}$	−0.062	−0.023	−0.018	0.024	−0.031	−0.014
	(0.002)	(0.0004)	(0.0006)	(0.001)	(0.001)	(0.001)
$s_{st+1} - s_{st}$	1.000	0.174	0.198	0.138	0.488	0.002
	(0.023)	(0.005)	(0.007)	(0.012)	(0.014)	(0.016)
R^2	0.05	0.11	0.05	0.02	0.07	0.00
$\sigma(\times 100)$	0.95	0.22	0.31	0.51	0.56	0.65

The table presents estimates from six regressions each having the form described in equation (2). In the first column, five-year changes in a state's share of industry employment are regressed on the "excess" share of employment in that industry in the state in the initial year and a measure of state growth. The next five columns report similar regressions for dependent variables that are the portion of the total five-year change attributed to events at each of five stages of the plant life cycle. Standard errors are in parentheses.

equation (2). For the new firm birth and old firm birth regressions, the coefficient on $s_{ist} - s_{st}$ is negative, indicating that there is mean reversion in employment shares: employment in new plants (especially those belonging to new firms) increases less than one-for-one with state-industry employment. The coefficient on initial excess employment is positive in the plant closure regression, indicating that plants are less likely to close in states that have a higher than expected share of the industry's employment. (The dependent variable is negative in this regression.) For expansions and contractions, the β coefficient is also negative, implying that growth rates are lower in states with a high initial concentration in the industry. New firms are more likely to start away from current geographic centers of the industry, and growth is faster away from those centers, but the risks appear to be higher in the periphery and closures are also higher there.

Table 6 reports the portions of the change in the approximate EG index, $\bar{\gamma}_t$, which we attribute to each of the life cycle stages. These changes are listed as a percentage of initial concentration in the set of industries; that is, the table reports values of $100\Delta\bar{\gamma}^j_t/\bar{\gamma}_t$. Again, new firm births consistently have the effect of reducing the degree to which industries are geographically concentrated. On its own, the deagglomerating effect of new firm births can account for approximately three-fourths of the observed decline in geographic concentration over the last twenty years. Although plants opened by preexisting firms are comparable to new firm births in their total employment, they have less of a deagglomerating effect: they reduce geographic concentration in only three of the four five-year periods. On average, their effect is only a little more than one-third as large as the effect of new firm births.

Consistent with our previous finding that net expansions are lower in areas with an excess concentration of employment in an industry, we find that net expansions also tend to reduce geographic concentration. The magnitude of this effect is roughly comparable to that of new firm births. The one growth process that appears to reinforce geographic concentration is the closure process. Given that plant closures have not been explicitly discussed in the existing

theoretical literature on geographic concentration, this result particularly merits attention.[18]

B. Changing Patterns over Time

One of our initial observation from table 1 was that the trend toward industries being less geographically concentrated has been more pronounced in the second half of our sample than in the first. The average across industries of the value of the EG index was 0.039 in 1972, 0.038 in 1982, and 0.034 in 1992. From table 6, we see that this change is largely attributable to the fact that differing plant closure rates ceased to reinforce initial concentrations and to an increased tendency for plant expansions to occur away from industry centers. The effect of new plant births has been fairly constant throughout the period we study.

C. Differences across Industries

Table 7 reports the results of performing the same life cycle decomposition calculation for various subsets of industries. In this calculation, we have chosen to measure agglomeration in these industries relative to the same baseline state shares s_{st} as we used in the full sample.[19] In each

[18] In preliminary work we obtained similar results when examining three- and four-digit industries. All stages other than plant closures were found to reduce agglomeration, and new firm births had the largest deagglomerating impact. The regression on which our decomposition is based does not have controls for differences in the age and size of plants. Plants in industry centers tend to be older and larger than the average plant in an industry, and hence one might expect them both to grow more slowly and to be less likely to close. Table 8 of Dumais, Ellison, and Glaeser (1997) presents regressions (using MSA-level data) that indicate that the finding that plants in industry centers are less likely to close is robust to the inclusion of controls for a plant's age and size, but that these controls may account for the slower growth of existing plants in industry centers. Our finding that new and old firm births increase substantially less one-for-one with initial employment also comes through clearly in the MSA-level regressions.

[19] Because s_{st} is not the average of the state-industry shares across the industries in the subsample, the portions of the total change attributed to each of the life cycle stages will not add up, even in an approximate sense. We felt, however, that this was preferable to setting the s_{st} equal to the mean shares within the subsample, as this would implicitly be defining, agglomerated to mean that a textile industry's employment distribution differed from that of the typical agglomerated textile industry. This would make us regard a textile industry that was evenly spread throughout the United States as agglomerated, for example.

TABLE 6.—LIFE CYCLE DECOMPOSITION OF CHANGES IN GEOGRAPHIC CONCENTRATION

Time Period	Percentage Change in $\bar{\gamma}_t$	Percentage Change in $\bar{\gamma}_t$ Attributed to:				
		New Firm Births	Old Firm Births	Closures	Expansions/Contractions	Switches
1972–1977	0.4	−2.1	−1.8	2.9	−0.7	2.2
1977–1982	−2.7	−2.8	−0.8	2.6	−2.8	1.2
1982–1987	−5.9	−2.3	−1.2	−0.1	−2.4	0.2
1987–1992	−4.7	−2.7	0.2	0.6	−2.9	0.4
Average of estimates	−3.2	−2.5	−0.9	1.5	−2.2	1.0

The first column of the table gives the percentage change over each five-year period of the average (across 134 three-digit manufacturing industries) of the $\bar{\gamma}$ measure of geographic concentration. The final five columns decompose these changes into portions attributable to events at various stages of the plant life cycle. The decomposition is described in subsection IIC.

case, we report the average of the effect in each of the four five-year periods.

The first row of table 7 repeats the average results from table 6. The second and third rows look separately at the most geographically concentrated one-third and the least geographically concentrated one-third of industries (in terms of 1972 values of the EG index). Our main conclusion here is that the full sample results are also representative of what has happened within the highly geographically concentrated industries. In the nonlocalized industries, new firm births and expansions have not had a deagglomerating effect, and levels of geographic concentration have increased (albeit only slightly given that the base to which the percentages apply is very small.)

The final four rows of the table describe the behavior of the same four subsamples of the set of highly geographically concentrated industries that we discussed in subsection IVB in connection with table 3. The life cycle pattern of the location of the high-tech industries differs somewhat from the overall pattern: both the openings of new plants by existing firms and the net expansions that have occurred in existing plants have had stronger deagglomerating effects here than in the average industry. There also seems, however, to have been a greater difference between plant closure rates in and away from industry centers, so, in the aggregate, geographic concentration in these industries has decreased only a bit more than in the typical industry.

The textile and apparel industries stand out for having become more geographically concentrated over the last twenty years. The largest part of this difference is attributable to net expansions acting to reinforce geographic concentration, with plant births (to new and old firms) also having less of a deagglomerating effect than in the full sample.

VI. Conclusion

The geographic concentration of industries is the result of a dynamic process in which the combination of plant births, closures, and expansions/contractions act together to maintain a slow-changing level of industrial concentration. Existing theories of industrial location have dynamic, as well as static, implications, and that data on the dynamics of plant locations can offer valuable information about the relevance of different theories.

One of our more striking findings is that many geographically concentrated industries do not exhibit any less mobility than a typical unconcentrated industry. Although historical accidents (as stressed by Arthur (1986) and Krugman (1991a)) may have long-lasting effects in the textile industries, they are not so important in high technology and many other industries. We regard the stability of geographic concentration despite industry mobility as strong evidence that levels of geographic concentration are determined by fundamental industry characteristics.

A second finding is that new plant births tend to act to reduce geographic concentration. The benefits from within-industry spillovers on new plant formation apparently do not have a sufficiently strong effect to maintain concentration levels by themselves. The dispersion of new plants is perhaps more in line with the Jacobs view of the importance of diverse factors in generating new businesses, but existing theories have really not focused on the effects of externalities at different stages of a plant's life and do not account well for our view of the plant closure process as maintaining concentration.

These patterns are just the broadest regularities in our data. As we've noted, there are many different patterns in different industries and in different time periods—some

TABLE 7.—LIFE CYCLE DECOMPOSITIONS FOR VARIOUS SUBSETS OF INDUSTRIES

Set of Industries	Average Percentage Change in $\bar{\gamma}_t$	Percentage Change in $\bar{\gamma}_t$ Attributed to:				
		New Firm Births	Old Firm Births	Closures	Expansions/Contractions	Switches
Full sample	−3.2	−2.5	−0.9	1.5	−2.2	1.0
Geographically concentrated	−2.2	−3.1	−1.3	2.5	−2.6	1.2
Geographically unconcentrated	4.9	−0.0	1.6	1.3	0.4	2.4
Concentrated high technology	−4.1	−1.8	−2.7	5.1	−5.6	0.8
Concentrated natural resource	−8.3	−3.2	−0.7	0.4	−3.9	0.8
Concentrated textile & apparel	0.9	−1.5	0.3	0.4	0.5	1.9
Concentrated crafts	−0.1	−4.3	−0.7	2.5	−1.6	3.0

The table provides decompositions of percentage changes in geographic concentration into portions attributable to events at various stages of the plant life cycle for different subsets of industries.

compatible with many theories and some seemingly at odds with much of what has been written. In recent years, authors have tried to model the dynamics of agglomeration as well as describing it as an equilibrium outcome.[20] Our hope is that increased knowledge of the actual dynamic patterns will spur research both on the traditional models and in this area.

An obvious topic for future empirical research is to attempt to distinguish between different explanations for agglomeration. One thought we've had is that, although the various theories of agglomeration have all been designed to produce the prediction that industries will be agglomerated, they have different predictions for which industries will be coagglomerated, which areas that are not now industry centers will be fertile areas for new firm births, and so on. We are exploring these ideas in ongoing work.

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APPENDIX

In this appendix, we provide a more complete derivation of the life cycle decomposition of changes in the average plant Herfindahl.

Let e_{ikt} be the employment level in the kth plant in industry i at time t. Define $z_{ikt} \equiv e_{ikt}/\Sigma_k e_{ikt}$, $\Delta z_{ikt} \equiv z_{ikt+1} - z_{ikt}$, and $\tilde{z}_{ikt} \equiv z_{ikt} - \frac{1}{N_i}$, where N_i is the number of plants that operate in the industry either in period t or in period $t + 1$.

If one runs a regression with employment changes within each plant-industry as the dependent variable on the sample of plant-industries that have positive employment either in period t or period $t + 1$

$$z_{ikt+1} - z_{ikt} = \hat{\alpha} + \hat{\beta}\tilde{z}_{ikt} + \hat{\epsilon}_{ikt}, \tag{A1}$$

the estimates will always satisfy $\hat{\alpha} = 0$, $\Sigma_{ik}\,\hat{\epsilon}_{ikt} = 0$, and $\Sigma_{ik}\,\tilde{z}_{ikt}\hat{\epsilon}_{ikt} = 0$. (Note that we say "plant-industry" just to indicate that there's one observation on each plant for each industry to which it belongs in either time period of the pair; a plant that has switched industries between t and $t + 1$ thus has its experiences recorded in two observations in the regression.)

Changes in H_t are related to the regression coefficients by

$$H_{t+1} - H_t = (2\hat{\beta} + \hat{\beta}^2)\left(H_t - \frac{1}{I}\sum_i \frac{1}{N_i}\right) + \frac{1}{I}\sum_{ik}\hat{\epsilon}_{ikt}^2$$

To see this, we simply note that $\Sigma_k\,\tilde{z}_{ikt}^2 = \Sigma_k\left(z_{ikt} - \frac{1}{N_i}\right)^2 = H_{it} - \frac{1}{N_i}$, and then substitute the regression equation into the plant Herfindahl formula:

$$H_{t+1} - H_t = \frac{1}{I}\sum_{ik}\tilde{z}_{ikt+1}^2 - \tilde{z}_{ikt}^2$$

$$= \frac{1}{I}\sum_{ik} 2\Delta\tilde{z}_{ikt}\tilde{z}_{ikt} + \Delta\tilde{z}_{ikt}^2$$

$$= \frac{1}{I}\sum_{ik} 2(\hat{\beta}\tilde{z}_{ikt} + \hat{\epsilon}_{ikt})\tilde{z}_{ikt} + (\hat{\beta}\tilde{z}_{ikt} + \hat{\epsilon}_{ikt})^2$$

$$= \frac{1}{I}(2\hat{\beta} + \hat{\beta}^2)\sum_{ik}\tilde{z}_{ikt}^2 + \frac{1}{I}\sum_{ik}\hat{\epsilon}_{ikt}^2$$

$$= (2\hat{\beta} + \hat{\beta}^2)\frac{1}{I}\sum_{ik}\left(H_{it} - \frac{1}{N_i}\right) + \frac{1}{I}\sum_{ik}\hat{\epsilon}_{ikt}^2.$$

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[20] Krugman and Venables (1995), Holmes (1999), and Krugman, Fujita, and Mori (1999) are notable examples of explicitly dynamic models.

Let

$$\Delta z_{ikt}^{j} = \frac{\Delta e_{ikt}^{j} - z_{ikt}\Delta E_{it}^{j}}{E_{it+1}}.$$

If we estimate separate regressions for each of the J components of changes in the plant-industry employment shares,

$$\Delta z_{ikt}^{j} = \hat{\alpha}_{j} + \hat{\beta}_{j}\bar{z}_{ikt} + \hat{\epsilon}_{ikt}^{j},$$

the estimates will be related to the estimates obtained from the regression (A1) of overall share changes by $\hat{\beta} = \Sigma_{j} \hat{\beta}_{j}$ and $\hat{\epsilon}_{ikt} = \Sigma_{j} \hat{\epsilon}_{ikt}^{j}$. The fact that the ΔH_{t}^{j} defined in equation (4) in the text satisfy $H_{t+1} - H_{t} = \Sigma_{j} \Delta H_{t}^{j}$ then follows immediately from the expression for $H_{t+1} - H_{t}$ given previously.

Again, the definition can be motivated by regarding the formula as attributing to events in the jth category both the change in the plant Herfindahl that would have resulted if those events were the only employment changes and a portion of the additional change in the Herfindahl that results from the correlation between events of the jth and other types. In thinking about correlation here (and if one wants to think about mean reversion and randomness), it is important to keep in mind that the relevant correlations here are only those at the level of the individual plant.