INDUSTRIAL CONCENTRATION AND REGIONAL GROWTH: EVIDENCE FROM THE PREFECTURES

Robert Dekle

Abstract—In this paper, we estimate the impact of dynamic externalities, using direct measures of total factor productivity (TFP) growth at the regional level. We find that, at the one-digit level, significant dynamic externalities exist for the finance, services, and wholesale and retail trade industries, but—contrary to the findings of most previous research—these externalities do not exist for the manufacturing industry.

I. Introduction

SEVERAL recent explanations of economic growth focus on increasing returns to scale external to the firm as a source of increasing productivity (Romer, 1986; Lucas, 1988). Because these externalities arise from the interaction of economic agents, these effects should be most pronounced when agents are in close physical proximity. Indeed, Lucas (1988) notes the similarity of his explanation of economic growth and the explanation for cities.

A growing body of research in recent years have tried to estimate the extent and type of dynamic externalities, using data for cities (Glaeser, Scheinkman, & Shleifer, 1992, 1995; Henderson, Kuncoro, & Turner, 1995; Kim, 1995; Simon, 1998; Glendon, 1998; Gordon, Richardson, & Yu, 1998). Despite the different data sources used, their methodologies are similar: this research has invariably examined the distributions of employment growth both over time and over different cities. From the dependence of these distributions on historical conditions, this research has also tried to infer the impact of dynamic externalities on productivity growth. This research has found that the kinds of externalities found in cities are generally important for employment and thereby productivity growth. However, as we explain later, this inference of productivity growth from employment growth can be problematic. For one thing, people may move to different cities for weather, schools, and other reasons unrelated to the productivities of those cities. As first noted by Glaeser et al. (1992), it is far better to have a direct measure of the productivity of cities, but the lack of output and capital at the city level has impeded this direct measurement in the United States.

In this paper, we estimate the impact of dynamic externalities, using direct measures of total factor productivity (TFP) growth at the regional level. To the best of our knowledge, this paper is the first to estimate dynamic externalities at the regional level, using direct measures of TFP growth. We obtain these direct measures of TFP growth using Japanese prefectural data, from which output data are available and the capital stock can be calculated. We can use Japanese prefectural data because Japanese prefectures have much higher densities than U.S. states and are more like U.S. cities. We find that, at the one-digit level, significant dynamic externalities exist for the finance, services, and wholesale and retail trade industries, but, contrary to the findings of most previous research, these externalities are nonexistent for the manufacturing industry. Finally, we show that our main results are robust to pooled (panel) data estimation.

Using the terminology of Glaeser et al. (1992), there are three types of dynamic externalities. The Marshall-Arrow-Romer (MAR) externality concerns knowledge spillovers among firms in an industry. This view says that the concentration of an industry in a region helps knowledge spillovers between firms, and therefore productivity growth of that industry. In contrast, Jacobs (1969) externalities derives from a buildup of knowledge or ideas associated with historical diversity. Jacobs’s theory predicts that industries located in areas that are highly industrially diversified should grow faster. Finally, Porter (1990), like MAR, argues that industrial concentration stimulates growth, but that local competition (rather than local monopoly) fosters innovation and the dissemination of information.

In this paper, we find no dynamic externalities of any type in manufacturing; strong MAR externalities, but no Jacobs or Porter externalities for finance; and relatively strong MAR externalities, nonexistent Jacobs externalities, and some Porter externalities for the services industry and the wholesale and retail trade industry. When all nine one-digit industries are taken together (pooled results), there is some evidence of MAR and Porter externalities, but no evidence of Jacobs externalities.

This paper is organized as follows. In section II, we explain our methodology of calculating regional TFP growth and of estimating dynamic externalities. We show that inferring TFP from the value of marginal product equals wage equation (as done by previous researchers) can result in various biases. In section III, we explain our data and the construction of variables. In section IV, we depict the industry-by-industry and pooled-industry results of the paper. Section V concludes.

II. Dynamic Externalities

We examine TFP growth between 1975 and 1995 for nine Japanese one-digit industries: mining, manufacturing, construction, electricity/gas, wholesale and retail, finance/insurance, real estate, transportation, and services.

The starting point in the estimation of dynamic externalities is the measurement of TFP, $A_t$, from the usual growth-
accounting exercise. Assume a production function that is constant returns to scale (at the firm level) in capital and labor:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha},$$  \hspace{1cm} (1)

where $K_t$ is the level of the capital stock of industry $i$ in the region at time $t$, $L_t$ is the number of workers in industry $i$ in the region at time $t$, and $A_t$ is the region-specific TFP level of industry $i$.

The growth in region-specific TFP between time $t$ and $t-1$ of industry $i$, $gr(A_{t-1,i})$, is measured in the usual way as (suppressing industry subscripts):

$$gr(A_{t-1,i}) = \ln \left( \frac{Y(t)}{Y(t-1)} \right) - \alpha \ln \left( \frac{K(t)}{K(t-1)} \right) - (1-\alpha) \ln \left( \frac{L(t)}{L(t-1)} \right).$$  \hspace{1cm} (2)

To test for dynamic externalities, we model $gr(A_{t-1})$ as a function of historical (1975) conditions in regions. In particular, as arguments of $gr(A_{t-1,i})$, we include the following variables: the own industry concentration of output or employment, $p_{0i}$; an index of the diversity of other industries that may affect an industry’s productivity, $D_{0i}$; and $C_{0i}$, an index of local competition of an industry. These variables are assumed to represent MAR, Jacobs, and Porter externalities, respectively. In addition, the log TFP level in 1975, $\ln(\text{A}_{1975})$, is included as an initial condition (IC), to capture the possibility of mean reversion. In sum, we obtain our estimating equation:

$$gr(A_{t-1,i}) = g(p_{0}, D_{0}, C_{0}, IC).$$  \hspace{1cm} (3)

Because of the lack of capital stock and output data at the city level for the United States, earlier researchers (Glaeser et al., 1992; Henderson et al., 1995; Miranda, 1995; Kim, 1995; Glendon, 1998) could not perform the growth-accounting exercise of equation (2) to directly measure $gr(A_{t-1,i})$. Rather, these researchers indirectly attempted to infer the extent of dynamic externalities from the growth in city employment and wages, from the value of marginal product equals wage equation. From the production function (equation (1)), labor market equilibrium means that $p_t (1 - \alpha) A_t K_t^{\alpha} L_t^{1-\alpha} = w_t$.

Taking logarithms and rearranging provides

$$\ln \left( \frac{L(t)}{L(t-1)} \right) = -\frac{1}{\alpha} \ln \left( \frac{w(t)}{w(t-1)} \right) + \frac{1}{\alpha} gr(A_{t-1,i})$$  

$$- \ln \left( \frac{K(t)}{K(t-1)} \right) + \frac{1}{\alpha} \ln \left( \frac{p(t)}{p(t-1)} \right).$$

If capital stock data are unavailable,

$$\ln \left( \frac{L(t)}{L(t-1)} \right) = -\frac{1}{\alpha} \ln \left( \frac{w(t)}{w(t-1)} \right) + \frac{1}{\alpha} gr(A_{t-1,i})$$  

$$+ \frac{1}{\alpha} g(p_0, D_0, C_0, IC)$$  

$$+ \frac{1}{\alpha} \ln \left( \frac{p(t)}{p(t-1)} \right),$$

where equation (3) is used to substitute for $gr(A_{t-1,i})$.

At least three problems that do not arise in the estimation of externalities from equation (3) arise in the estimation of equation (4). First, unless the regional capital stock is constant, $\ln(\frac{K_i}{K_{t-1}})$, omitted-variables bias may plague the estimates. The constant regional capital stock assumption is unrealistic, even in relatively low-investment countries like the United States. Second, because the growth in regional prices (in $P_t$, $P_{t-1}$) by industry is usually unobserved, earlier researchers have had to assume some pattern for the growth in prices. For example, Glaeser et al. (1992) assume that the growth in prices is determined at the nationwide level and thus do not vary by city. To the extent that some goods are nontraded and that all manufactured goods include some nontraded component, the assumption of nationwide prices may be unrealistic. Third, it is well known that living costs such as housing rents and consumption amenities such as weather and local public goods affect migration decisions. Earlier research on dynamic externalities have usually not controlled for these amenities in the estimation of an equation like equation (4) (with the exception of Glaeser et al. (1995) and Glendon (1998) who explicitly control for local amenities). All of these difficult issues are avoided when TFP growth is estimated directly in equation (3). However, for comparability with earlier studies, we also show the results when the marginal-revenue-product-equals-wage-equation like equation (4) is estimated.

### III. Construction of Data

The data pertain to 1975 and 1995 and are mainly from the 1998 edition of the Japanese Annual Report on the Prefectural Accounts (ARPA), published by the Economic Planning Agency. This publication is unique in that it includes at the regional level (47 Japanese prefectures) all of the data contained in conventional national income accounts.

To calculate TFP, we need output, the supplies of labor and capital, and the labor and capital shares, all by industry. As a measure of industry output, we use NNP at factor cost (GNP minus indirect business taxes minus depreciation). As a measure of industry labor supply, we take the number of employed persons by industry from the Labor Force Survey (published by the Ministry of Labor) and multiply this...
number by the average hours of worked by industry (from the *Basic Survey on the Wage Structure*, published by the Ministry of Labor). As a measure of the industry capital stock, we divide the amount of industry capital depreciation (from factor income tables) by the industry capital depreciation rate (from the Ministry of Labor). As a measure of the industry capital stock, we take the share of employee compensation in NNP at factor cost. The industry output is the share of industry labor share. The industry output and capital stock are deflated by the industry GDP deflator for each prefecture (from ARPA).

As explanatory variables, we need base year (1975) levels of $p_i$, $D_i$, $C_i$, and $w_i$. For base-year concentration, $p_i$ (MAR externalities), we take the ratio of own-industry output or own-industry employment to the total effective urban land area (in square kilometers). The effective urban land areas represent about 12% of the total land areas in Japan, and almost all industrial activity are concentrated in these areas. Output per square kilometers is preferable to employment per square kilometer as a measure of density because it better captures the intensity of labor, human, and physical capital combined relative to physical space. Also, we define the Hoover-type (1936) variable,

$$\rho_i = \frac{y_{i0}}{y_{i0} + y_i},$$

where $y_{i0}$ is the industry output or employment in the region, $y_{i0}$ is the total output or employment in the region, $y_{iJ}$ is the industry output or employment in Japan, and $y_J$ is total output or employment in Japan.

As noted by Glaeser et al. (1992), this Hoover-type variable measures how specialized a city is in an industry relative to what one would expect if output or employment in that industry was scattered randomly across Japan.

For the index of diversity, $D_i$ (Jacobs externalities), we follow Henderson et al. (1995) and calculate the Herfindahl-Hirschman Index (HHI) for each region using all of our nine one-digit industries:

$$D_i = \frac{1}{9} \sum_{i=1}^{9} s_i^2$$

where $s_i$ is the share of industry $i$ output or employment in all other output or employment in the region.

As a measure of local competition, $C_i$ (Porter externalities), following Glaeser et al. (1992), we define

$$C_i = \frac{y_{i0}}{y_{i0} + f_i},$$

where $f_i$ is the number of firms in the industry in Japan. A value of $C_i$ greater than 1 means that the industry has fewer firms relative to its size in this region than it does in the rest of Japan; that is, the industry is less competitive. The number of establishments and the number of employees by establishment at the industry level are from the *Establishment Census*, published by the Management and Coordination Agency. Finally, as a measure for the industry wage, $w_i$, we divide employee compensation from the ARPA by our measure of industry labor supply. We then divide this industry wage by the industry GDP deflator.

Table 1 depicts the means over the 47 prefectures of several key variables. For most industries, the average growth rates of the prefectural capital stock and total factor productivity closely match the national growth rates (Ministry of Labor, 1997).

### IV. Results

In this section, we show the results of our estimation of the nature and extent of external economies (MAR, Jacobs, and Porter). Although we have performed the estimation on all nine industries at the one-digit level, to save space and for comparability with earlier research our discussion here focuses on just four industries: finance, manufacturing, wholesale and retail, and services.
The main results, the impact of dynamic externalities on TFP growth (equation (3)) are shown in table 2. To control for mean reversion in the level of TFP, we include as an initial condition the level of log (TFP) in 1975 (not shown). The sign of log (TFP) is always negative and usually highly significant, suggesting the presence of mean reversion, which is a finding consistent with Glaeser et al. (1992) and Henderson et al. (1995). Although more than fifty different specifications were tried for each industry, table 2 depicts four specifications that are representative to save space. The coefficient signs and significance of the variables of interest were highly robust to the different specifications.

The most remarkable results in table 2 relate to the heterogeneity across industries in the type and extent of externalities. The finance industry is characterized by high own-industry agglomeration economies (MAR externalities): the initial level of the own-industry GDP density raises subsequent industry TFP growth. An increase of one standard deviation in finance GDP density raises TFP growth by 0.5% per year. However, the diversity of industries (Jacobs externalities) and the degree of local competition (Porter externalities) have no apparent effect on productivity growth in finance.

The presence of strong dynamic externalities in finance is consistent with Dekle and Eaton (1999), who find in Japanese regional data that agglomeration economies are far more geographically concentrated in finance than in manufacturing. The extent of human capital externalities may explain why agglomeration effects in finance are more localized. One can imagine that human interactions would be more important in raising productivity in financial services than in manufacturing. For one thing, financial services are more knowledge intensive: in Japan, 36% of workers in the financial sector have a university education, whereas in manufacturing the figure is only 15%.

In contrast, the manufacturing industry is characterized by the absence of external economies of any type. Besides the control variable, none of the coefficients are significant. This result goes against earlier research that estimated equation (4) and found significant MAR externalities for manufacturing industries at the two-digit level or lower. Taken together, the results from the earlier research and ours suggest that it may be problematic to infer productivity growth from employment growth, and that manufacturing as a whole is actually characterized by low or no dynamic externalities. Alternatively, if manufacturing dynamic externalities are present, they are MAR and are confined to rather narrow industry categories at the two-digit level or below (such as software or ball-bearing manufacturing), and that spillovers among these product categories (Jacobs externalities) are rather limited.

The services industry and the wholesale and retail trade industry are both characterized by relatively strong MAR externalities, nonexistent Jacobs externalities, and some Porter externalities. An increase of one standard deviation in own-industry GDP density raises TFP growth in services and in the wholesale and retail trade industries by 0.4% and 0.5% per year, respectively.

The presence of dynamic externalities in nonmanufacturers such as the services and the wholesale and retail industries is consistent with Glaeser et al. (1992), who find that dynamic externalities are, if anything, more pronounced in these industries than in manufacturing. Given that these industries produce mostly nontraded goods, for employees in these industries, opportunities for human interaction with people outside of the prefecture are probably quite limited (Losch, 1967). Thus, opportunities for human interaction within the prefecture, which is associated with own-industry concentration, may be more important in these industries. Also, in industries producing nontraded goods, the main source of competition is within the prefecture, which may explain the importance of Porter externalities for these industries. For manufacturing and finance, much of the source of competition that spurs innovation may come from outside the prefecture.

It may seem surprising that dynamic externalities are important in the wholesale and retail industry because employees in this industry are not typically thought of as well educated. However, employees in this industry actually are quite well educated. (More than 26% have a college degree, compared to only 15% in manufacturing.) Moreover, Koike (1984) and others have argued that, in Japan, much of human capital accumulation occurs not by formal education but by on-the-job training. To test for the importance of human capital acquired on-the-job in the wholesale and retail industry, we divided the workers in this industry into “full-time” and “part-time.” Full-time workers have spent most of their careers in the industry, and their on-the-

### Table 2.—Region-Industry Total Factor Productivity Growth Between 1975 and 1995 (Ordinary Least Squares)

<table>
<thead>
<tr>
<th>Specification</th>
<th>Finance (1)</th>
<th>Manufacturing (2)</th>
<th>Services (3)</th>
<th>Wholesale and Retail (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP per sq. km. (coefficient × 1000)</td>
<td>0.089 (3.3)</td>
<td>0.089 (3.5)</td>
<td>0.0022 (0.2)</td>
<td>0.0049 (2.4)</td>
</tr>
<tr>
<td>Herfindahl-Hirschman Index (output)</td>
<td>−0.89 (−1.5)</td>
<td>−0.58 (−0.7)</td>
<td>−0.86 (−1.9)</td>
<td>−0.17 (−0.3)</td>
</tr>
<tr>
<td>GDP per establishment in the region-industry relative to GDP per establishment in Japan</td>
<td>0.14 (1.4)</td>
<td>−0.19 (−1.3)</td>
<td>0.027 (0.5)</td>
<td>0.044 (0.7)</td>
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<tr>
<td>Initial conditions (IC): log (TFP) level in 1975.</td>
<td>47 observations (prefectures).</td>
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</table>

The table includes the impact of dynamic externalities on TFP growth (equation (3)) as shown in table 2. To control for mean reversion in the level of TFP, we include as an initial condition the level of log (TFP) in 1975 (not shown). The sign of log (TFP) is always negative and usually highly significant, suggesting the presence of mean reversion, which is a finding consistent with Glaeser et al. (1992) and Henderson et al. (1995). Although more than fifty different specifications were tried for each industry, table 2 depicts four specifications that are representative to save space. The coefficient signs and significance of the variables of interest were highly robust to the different specifications.
job human capital is much higher than those of part-time workers, who are mostly housewives, with intermittent work histories. We again ran equation (3) including two variables for $p_{t0}$ (MAR externalities): “full-time” labor per squared kilometer and “part-time” labor per squared kilometer. The coefficient on full-time labor density was highly significant, but the coefficient on part-time labor density was small and insignificant (not shown), suggesting that dynamic externalities in the wholesale and retail trade industry are almost entirely due to the density of full-time, high-human capital labor.

Table 3 replicates, at the one-digit level, the marginal-revenue-product-equals-wage equation (4) that was estimated by most previous researchers at the two-digit level or below (Glaeser et al., 1992; Henderson et al., 1995; Miracky, 1995; Glendon, 1998). Consistent with the neoclassical theory of labor demand, the coefficient on the change in wages is negative and highly significant in all specifications (not shown). The coefficients on the MAR density variable (labor per squared kilometer) either are insignificant (finance, services, wholesale and retail) or are negative (manufacturing), implying the absence of MAR externalities. With the exception of the manufacturing industry, there is some evidence that competition raises the rate of productivity growth (Porter externalities). There is no evidence of Jacobs externalities for any industry. The negative coefficient on the MAR variable is consistent with Glaeser et al. (1992), who find that industry over representation hurts its employment growth. Our findings here of Porter externalities but weak Jacobs externalities are replicated in the earlier literature.

Our favored interpretation for the insignificant or negative MAR coefficients in these results (equation (4)) is omitted-variables bias. Suppose that higher density results in, and is positively correlated with, higher capital stock growth. Then, if equation (4) is estimated with capital stock growth omitted, the coefficient on the density variable will be biased downwards, by standard omitted-variable arguments (Goldberger, 1968).

A. Panel Estimates

By pooling all nine industries, we can estimate the coefficients on the externality measures using panel data techniques. Panel data estimation can improve the precision of the estimates by increasing the number of observations. Also, with panel data, we can control for unobserved prefectural fixed effects, which can bias the coefficient estimates.

Table 4 depicts the panel data estimation of equation (3). The GDP density variable is highly significant: an increase of one standard deviation in own-industry GDP density raises TFP growth by about 0.4% per year. The HHI has the wrong sign, but the local competition variable is significant. Thus, the pooled results show that Japanese industries, taken together, exhibit some evidence of MAR and Porter externalities, but no evidence of Jacobs externalities.

Table 4 also depicts the panel data estimates of the marginal-revenue-product-equals-wage equation (4). These results essentially reproduce with Japanese data the results found in Glaeser et al. (1992), who in fact pool their six industries over 170 U.S. cities. As in Glaeser et al., the Hoover-type concentration measure is strongly negative, and the variable measuring Jacobs externalities is highly positive and significant. However, as we have already pointed out, there are potential pitfalls in inferring agglomeration effects from an equation such as equation (4).

In sum, the panel data estimation supports our earlier findings that agglomeration effects, if present, are of the MAR and the Porter types. However, as shown in tables 2 and 3, there is substantial heterogeneity among the industries. As noted by Hsiao and Sun (1999) and others, when the data-generating process is heterogeneous, pooling the data can yield highly misleading inference. Thus, although the results presented in table 4 are informative, we should place more weight on the individual industry estimates presented earlier.

### Table 3.—Region-Industry Employment Growth Between 1975 and 1995 (Ordinary Least Squares)

<table>
<thead>
<tr>
<th>Specification</th>
<th>Finance (1)</th>
<th>Finance (2)</th>
<th>Finance (3)</th>
<th>Finance (4)</th>
<th>Manufacturing (1)</th>
<th>Manufacturing (2)</th>
<th>Manufacturing (3)</th>
<th>Manufacturing (4)</th>
<th>Services (1)</th>
<th>Services (2)</th>
<th>Services (3)</th>
<th>Services (4)</th>
<th>Wholesale and Retail (1)</th>
<th>Wholesale and Retail (2)</th>
<th>Wholesale and Retail (3)</th>
<th>Wholesale and Retail (4)</th>
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</thead>
<tbody>
<tr>
<td>Labor per sq. km.</td>
<td>−0.17 (−0.5)</td>
<td>0.31 (1.1)</td>
<td>−0.26 (−4.5)</td>
<td>−0.27 (−4.8)</td>
<td>−0.12 (−0.9)</td>
<td>−0.0015 (−0.013)</td>
<td>−2.03 (−1.5)</td>
<td>1.97 (1.7)</td>
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<tr>
<td>Region-industry’s share of employment relative to industry’s share of Japanese employment</td>
<td>−0.47 (−1.9)</td>
<td>−0.71 (−4.4)</td>
<td>−0.054 (−0.3)</td>
<td>0.078 (0.68)</td>
<td>−0.42 (−1.4)</td>
<td>−0.81 (−3.6)</td>
<td>−0.69 (−4.9)</td>
<td>−1.1 (−5.4)</td>
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<tr>
<td>Herfindahl-Hirschman Index (employment)</td>
<td>−0.48 (−0.2)</td>
<td>2.1 (0.8)</td>
<td>0.039 (0.6)</td>
<td>0.041 (1.2)</td>
<td>3.87 (1.4)</td>
<td>0.61 (2.2)</td>
<td>0.77 (3.1)</td>
<td>0.66 (0.51)</td>
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<tr>
<td>Employment per establishment in the region-industry relative to employment per establishment in Japan</td>
<td>0.27 (2.3)</td>
<td>0.45 (4.2)</td>
<td>0.039 (0.6)</td>
<td>0.041 (1.2)</td>
<td>3.87 (1.4)</td>
<td>0.61 (2.2)</td>
<td>0.77 (3.1)</td>
<td>−0.28 (−2.3)</td>
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Initial conditions (IC): log (employment) level in 1975; log (change in wages) from 1975 to 1995. 47 observations (prefectures).
We have shown that, at the prefectural level, there is considerable heterogeneity among industries in how dynamic externalities affect productivity growth. We have shown that specialization raises productivity growth in the finance, services, and wholesale retail industries, and that competition helps growth in the manufacturing and wholesale retail industries. At the one-digit level, the concentration of GDP or employment does not affect manufacturing productivity, suggesting that the benefits to concentration in manufacturing are small.

The evidence suggests that the cross-fertilization of ideas is especially important for nonmanufacturers, and that there will be a tendency of further geographic concentration in industries such as financial services. The manufacturing industry is characterized by low or no dynamic externalities. Thus, the manufacturing industry should continue to disperse geographically, both domestically and internationally.

REFERENCES