I. Introduction

From its inception, the endogenous growth literature has stressed the role of information externalities in the growth process (Romer (1986); Lucas (1988)). Naturally, this has stimulated considerable interest in determining the economic environments most conducive to rapid information flows. Many scholars (Jacobs (1969), (1984); Bairoch (1988); Lucas (1988)) have noted that cities, which bring various economic agents into close proximity to one another, appear to be ideal settings for the rapid flows of ideas and innovations envisioned by the endogenous growth literature, and a number of recent studies have sought to examine empirically the types of cities most conducive to innovation and growth (Glaeser et al. (1992); Henderson et al. (1995)).[1]

Although these empirical studies have provided a number of important insights, their reliance on aggregate data raises the possibility of inconsistent estimates due to both simultaneity and aggregation biases. Furthermore, the dependent variable in these studies--employment growth--is not a very direct measure of either innovative input or output. Finally, as will be discussed further below, the fact that both the dependent variables and the regressors in these studies reflect outcomes of decisions made by profit-maximizing firms poses the problem of omitted variable bias.

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[1]In related work, Ciccone and Hall (1996), Kim (1995), and Mody and Wang (1997) examine the role of regional specialization and diversity on growth.

The present study tries to overcome each of these shortcomings. Our use of firm-level data removes the simultaneity and aggregation biases mentioned above. Furthermore, our dependent variable is the number of R&D scientists of the firm, a much more direct measure of innovative behavior than employment growth. Finally, the fact that our data is from China implies that city-level aggregates included as regressors were largely determined by bureaucrats rather than by profit-maximizing firms, thereby reducing the likelihood of omitted variable bias.

The literature on cities and their characteristics is vast, but Glaeser et al. (1992) provide a helpful summary of the three predominant theories concerning which types of cities best foster innovation, the three theories differing in their views of the impacts of both industrial specialization and monopoly on innovation. First, the Marshall-Arrow-Romer (MAR) view stresses the importance of information spillovers between firms within an industry, suggesting that cities which specialize in a particular industry are most likely to experience rapid productivity growth. At the same time, MAR stresses that it is important for firms to have some monopoly power in order to be able to appropriate the returns from their innovative activities.

The second view of Porter (1990) is similar to MAR in stressing the importance of within-industry spillovers for stimulating innovation,[2] but differs in its emphasis on local

[2]Von Hippel (1987) provides solid evidence of informal

competition rather than monopoly as an important inducement to innovative efforts. In addition to citing the classic work of Arrow (1962) about the advantages of competition in encouraging innovative efforts, Porter argues that firms in competitive environments are forced to innovate faster because a failure to do so will result in their extinction. Furthermore, he argues that local rivalry often stimulates innovative efforts simply because pride causes managers and workers to compete for recognition and "bragging rights" with their peers in other local firms.

The third predominant theory is due to Jacobs (1969), who argues that most knowledge spillovers to an industry emanate from firms outside of that industry. Hence, Jacobs believes that diversified economic environments are the most conducive to innovation, more specialized cities hampering the cross-fertilization of ideas from different types of work. Like Porter, Jacobs believes that competition is more conducive to innovation than monopoly because monopolists are often able to prevent firms with new methods or products from entering the market.

Glaeser et al. (1992) test these competing theories using data on industrial-level, employment growth between 1956 and 1987 for the six largest industries in each city in 1956. Pooling the observations across all cities and industries, Glaeser et al.

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trading of proprietary information amongst firms within the U.S. ministeel industry, a finding consistent with the views of MAR and Porter.

find evidence in support of the views of Jacobs: local diversity and competition are the most conducive to long-run innovation. However, these authors stress that they are examining mature industries in well-established cities, and they postulate that specialization may be conducive to innovation in new or more technologically-dynamic industries. In other words, they suggest an industry life-cycle may exist in which specialization stimulates innovation when the industry is young while diversity promotes innovation when the industry is more mature. However, these authors stress that an industry life-cycle of this nature would not be consistent with strict versions of the Porter and MAR theories in which within-industry knowledge spillovers lead to permanent, self-sustaining growth in cities.

Using a very similar methodology, Henderson et al. (1995) examine employment growth in five different capital goods industries in 224 U.S. cities from 1970 to 1987 and find that specialization is conducive to growth but that diversity is important for initially attracting new, high-tech industries. Hence, in contrast to the views of Glaeser et al. (1992), these authors suggest that diversity is more important at early stages in the industry life-cycle while specialization becomes more important as the industry matures, a result which seems to confirm the Porter and MAR theories that within-industry spillovers can be the long-run source of growth. Henderson et al. (1995) do not examine the roles of monopoly or competition in the growth process.

We examine the three hypotheses about the effects of cities on innovation using data on the numbers of research and development (R&D) scientists from 261 firms drawn from 27 industries in 8 Chinese cities. We believe that these data provide a unique opportunity to study relatively young firms in very technologically-dynamic setting. Roughly 50% of the firms in our data are less than 10 years old, and the average age is only 18 years. Furthermore, six of the eight cities in which our firms are located participated in China's "open door" policy, which provided firms in these cities with greater access to foreign investment, technology and trade. It is widely believed that cities included in the "open door" policy were a hotbed of new ideas for Chinese firms, and there is some empirical evidence suggesting that these ideas translated into high rates of economic growth.[3] Hence, in contrast to the mature industries studied by Glaeser et al. (1992), these data allow us to examine information externalities and firm behavior in a very dynamic, information-intensive setting at the start of the industrialization process.

Our methodology differs from that of previous studies in several important respects. First, while the three theories mentioned earlier deal primarily with the type of economic

[3]Jefferson et al. (1992) find that total factor productivity growth accounted for 27 percent of Chinese firms' output growth between 1980-1988. Furthermore, Mody and Wang (1997) find that industrial growth in China's coastal provinces, the primary beneficiaries of the open door policy, averaged 20 percent per annum from 1985-1989 as compared with 14.4 percent for the remainder of the country.

environment that stimulates firms to invest in innovation, due to data limitations the dependent variable in the previous studies is employment growth. Glaeser et al. (1992) and Henderson et al. (1995) present models relating hicksian technical change to employment growth, but our dependent variable, the number of R&D scientists, is a more direct measure of investments in innovation and more closely addresses the issues raised by the three theories mentioned earlier.[4]

Second, our use of firm-level data allows us to take city-level characteristics as exogenous in our regressions. Previous studies have regressed city-level aggregates on city-level aggregates, raising problems of simultaneity bias, although Henderson et al. (1995) report attempts to instrument for several of their regressors.

Third, the fact that, given sunk costs, these city-level aggregrates are largely the result of historical decisions made by bureaucrats rather than of profit-maximizing firms reduces the problem of omitted variable bias. For example, consider a case in which some factor unobserved by the econometrician but observed by firms, say infrastructure, makes city k a particularly profitable location for industry j. If firms are free to choose their locations, then profit-maximizing behavior would naturally lead a large number of firms in industry j to locate in city k, making city k relatively specialized in

[4]As is discussed in Section III, the firms in our sample devote a very high fraction of their resources to R&D activities.

industry j. Now this unobserved factor would also be a component of the error term in regressions of previous studies in which the dependent variable is industry-level employment growth in each city, thereby causing an upward bias in the coefficient on the specialization regressor since specialization is correlated with this unobserved factor. However, in our context this problem of omitted variable bias is mitigated because regressors such as specialization take on values which are largely the outcome of decades of government planning rather than the result of profit-maximizing decisions on the part of firms, such profit-maximizing decisions being permitted only very recently. In other words, existing industrial location patterns in China may have little or nothing to do with optimal industrial location patterns.

Of course, it is conceivable that government planners could have made efficient decisions, but Henderson (1988) finds that industrial location patterns in China are very different from those in more market-oriented economies, and as we shall see further below, our own examination of the data confirms his findings. In short, firms in China are simply not located in the patterns typically observed when firms are allowed to maximize profits over an extended period of time.

Fourth, our use of firm-level data also allows us to avoid biases which can occur when aggregate data are used and firms are heterogeneous (Dunne et al. (1989); Hamermesh (1989); Bresnahan and Raff (1991); and Davis and Haltiwanger (1992)).

Fifth, we believe our measure of the degree of local competition--each firm’s perceived elasticity of demand--has advantages over the measure used by Glaeser et al. (1992): the number of firms per worker in a city-industry relative to the national average. Glaeser et al. (1992) find that the coefficient on this variable is positive in their regressions and argue that this suggests that competition is conducive to growth; however, they admit that this result could simply indicate that small firms grow faster. We believe that a firm’s perception of the elasticity of demand for its products is a clearer measure of the level of competition it faces.

As we shall see below, the results lend support to the views of Porter: firms which face greater competition and which operate in cities specialized in their own industry tend to invest more in innovation, conditional on each firm’s expected growth in output. We do not address the issue of how each firm’s expected growth in output may itself respond to the degrees of specialization and competition. Furthermore, we find evidence that specialization increases in importance as a firm ages. While firm age is not identical to the maturity of the industry, these results do lend support to the conclusions of Henderson et al. (1995) that the importance of specialization increases as an industry matures, i.e that within-industry knowledge spillovers can act as an "engine" of permanent, self-sustaining growth.

The remainder of the paper is as follows. Section II outlines the model of firm behavior and derives the estimating equation. Section III describes the data and variable construction. Section IV describes the estimation procedure and presents the results. Finally, Section V concludes the paper with some comments.

II. Model

We assume that each firm i faces a downward sloping demand curve at time t of the following form:[5]

$$P_{it} = A_{it} + K_{it} - h(Q_{it}) \tag{1}$$

where P_{it} is the price received by firm i for selling its output; A_{it} is a random intercept, representing a shock to firm i's demand at time t; K_{it} is the appropriable knowledge of firm i at time t, and h( ) is a monotonically increasing function of output, Q_{it}. This specification reflects the assumption that knowledge leads to new and improved products, thereby increasing the demand for the output of the firm to the extent that the firm is able to appropriate the returns from this knowledge.[6]

We assume that the stock of appropriable knowledge, K_{it}, is the summation of current and past increments to appropriable

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[5]Observers agree that by 1992, the year of our data, the economic reforms introduced in China in the late 1970s had resulted in considerable autonomy in decision-making for firm managers and that incentives were such that profit maximization is not an unreasonable assumption to make about firm behavior (Gordon and Li (1991); Byrd (1992); Jefferson et al. (1992); Perkins (1994)).

[6]Several studies have documented that the focus of R&D in Chinese firms is on producing new and improved products. See Jefferson and Rawski (1994) for a brief review.

knowledge, I_{it}:

$$K_{it} = \sum_{j=0}^{\infty} (1 - \delta)^j I_{it-j} \tag{2}$$

with I_{it} defined by:

$$I_{it} = \phi' Z_{it} R_{it} \tag{3}$$

where ϕ is an m$\times$1 vector of parameters; Z_{it} is an m$\times$1 vector of firm, industry, and city characteristics, including the degree to which the city is specialized, diversified, and competitive from the point of view of the individual firm; and R_{it} is the firm's R&D at time t.[7] The variables in Z_{it} and the associated parameters in ϕ determine how effective the firm's R&D is in increasing its appropriable knowledge base and thus its price. For example, if it is more difficult for a firm to appropriate the benefits of its R&D in a competitive environment, then the element of ϕ which multiples the competition variable would be negative. Similarly, if R&D is more productive in an environment in which there are large, within-industry spillovers resulting from a high level of industrial specialization, then the element of ϕ which multiplies the specialization variable would be positive. Of course, it is possible that spillovers could increase the firm's technological capability and price directly

[7]As we shall see further below, the firms in our sample devote a very high fraction of their resources to the performance of R&D.

apart from their interaction with the firm's own-R&D. However, this modification would not effect the form of our final estimating equation and would contradict the considerable evidence that given their limited technological capabilities, firms in less developed countries must invest in R&D before they can benefit from the spillovers of others (for example, see Mowery (1983); Basant and Fikkert (1996); Fikkert (1997)).[8]

The firm's problem at time 0 is to choose the optimal amount of R&D to maximize the expected, present discounted value of profits:

$$\max \Pi = E_0 \sum_{t=0}^{\infty} \beta^t P_{it} Q_{it} - p_R R_{it} - C(R_{it}) - w_{i't} x_{it} \tag{4}$$

where p_R is the price per unit of R&D, x_{it} is a g$\times$1 vector of traditional inputs, and w_{it} is the associated g$\times$1 vector of input prices. $C(R_{it})$ is a quadratically increasing function of R&D, representing costs of adjustment or increasing costs of financing

[8] On their own, the specifications in equations (1)-(3) imply constant returns to scale to R&D at the firm level. Furthermore, if aggregate R&D enters Z through spillover effects, this would imply increasing returns to R&D at the aggregate level, consistent with the specification of Romer (1986). We do not have data on aggregate R&D to include in the vector Z. However, if the spillover variables we use in our estimations are functions of aggregate R&D, as we would expect, then the evidence we find of spillovers appears to imply increasing returns to scale to R&D in the aggregate. However, as we shall see in equation (5), our specification actually imposes decreasing returns to R&D each period at the level of the firm due to our assumption of adjustment costs to R&D. Whether the spillovers we find in our estimations are sufficiently strong to provide nondecreasing returns to R&D in the aggregate is a question we cannot answer with the present data.

R&D investments:

$$C(R_{it}) = \alpha_{it} R_{it} + \theta R_{it}^2 \qquad (5)$$

The coefficient on the linear term of the adjustment costs, α_{it}, is random, allowing firms to differ in their costs of doing R&D.

We assume that firms expect their output to grow according to the following process:

$$E_t[Q_{it+j}] = [\gamma g_i]^j Q_{it} \qquad (6)$$

where γ is a parameter and g_i is a variable expressing firm i's expectations about the rate of growth of output for its industry as a whole. We would expect that firms which anticipate rapid growth for their industry would expect higher growth for their own output as well, and this is confirmed in later estimates which find that γ is positive. Note that we are not assuming that output is exogenous. In fact, as will be discussed further below, we instrument for output in the estimates which follow. We are only assuming that output, which is assumed to be endogenous, follows the process indicated in equation (6).

Taking the derivative of the present discounted value of profits in equation (4) with respect to R_{i0} and setting equal to zero gives us the following estimating equation:

$$R_{i0} = -\rho + \psi' Z_{i0} Q_{i0} / (1 - \lambda g_i) + \varepsilon_{i0} \tag{7}$$

where $\rho = p_R / (2\theta)$, $\psi' = \phi' / (2\theta)$, $\lambda = \beta(1 - \delta)\gamma$, and $\varepsilon_{i0} = \alpha_{i0} / (2\theta)$, as long as $|\lambda g_i| < 1$. As will be discussed further below, equation (7) is estimated using weighted, nonlinear, two-stage least squares.

The intuition for equation (7) is clear. The term $\psi' Z_{i0} = \phi' Z_{i0} / (2\theta)$, and we see from equation (3) that $\phi' Z_{i0}$ represents the marginal increase in appropriable knowledge due to R&D at time 0. Furthermore, we see from equation (1) that a marginal increase in appropriable knowledge corresponds to a marginal increase in the price per unit. Clearly, the marginal benefit at time 0 of the R&D conducted at time 0 will then be the marginal increase in the price induced by the R&D times the number of units sold at time 0, i.e. $\phi' Z_{i0} Q_{i0}$. The fact that this marginal increase in appropriable knowledge--and hence in the price--decays over time, that the output over which the price applies grows over time, and that producers have a discount rate, give us an infinite, geometric series of discounted marginal benefits whose sum is represented by $\phi' Z_{i0} Q_{i0} / (1 - \lambda g_i)$. Dividing this figure by 2θ, a term representing the size of the adjustment costs, gives us $\psi' Z_{i0} Q_{i0} / (1 - \lambda g_i)$, the term in equation (7). Hence, the term in equation (7) can be viewed as the ratio of the present discounted value of the marginal benefits of R&D performed at time 0 to the adjustment costs. Clearly, as this ratio rises, R&D expenditures will rise.

III. Data and Variable Construction

The firm-level data come from a 1992 World Bank survey of 480 Chinese firms evenly divided amongst 8 cities. The original sample was chosen by ranking the firms in each city from highest to lowest in terms of their output. A firm from city c was then included in the sample if its rank in its city was one of the integers in the set $\{s_c, 2s_c, ...60s_c\}$ where s_c is found by dividing the total number of firms in city c by 60 and then rounding to the nearest integer. In this manner, the firms chosen from each city spanned the entire range of output in that city at intervals of 1/60. Out of this sample of 480 firms, complete data on all the regressors were available for only 261 observations.

Three of the cities--Fuzhou, Xiamen, and Quanzhou--are located in the coastal province of Fujian near the island of Taiwan. Similarly, three cities--Shenzhen, Guangzhou, and Dongguan--are located in the coastal province of Guangdong near the city of Hong Kong. In contrast, two of the cities--Chengdu and Chongqing--are located in the interior province of Sichuan. Unlike the coastal cities, these interior cities were not included in the "open door" policy, the result being that firms in these cities have had much less exposure to foreign investment and technology than firms in the coastal cities.

Data on the output of 27 manufacturing industries in each city were obtained from China Urban Statistics 1992. Table 1 reports the combined, aggregate output by industry for all eight cities along with the number of firms from each industry in the present sample.

It appears that China's history of economic planning has resulted in industrial location patterns quite different from those found in market economies. As discussed in Section I, this reduces the problem of omitted variable bias since we do not have a situation where city k is heavily specialized in industry j simply because there is some unobserved (to the econometrician) factor which makes profit-maximizing firms in industry j choose to locate in city k. Using data from several market-oriented economies in both the first and third world, Henderson (1988) finds that small- to medium-sized cities tend to be specialized, the industries in such cities being characterized by within-industry externalities (textile, apparel, transport equipment, primary metals, food processing, pulp and paper). Although cities specializing in such industries are large enough to provide for within-industry spillovers, their relatively small size reduces congestion and commuting costs. In contrast, some industries (high fashion apparel, upper-end publishing, and business services) benefit from overall urban scale and diversity and will seek to locate in larger, more diversified cities (see also Henderson et al. (1995)).

In contrast, as Table 2 indicates, there is no correlation between city size and industrial specialization for the eight cities examined here. For example, Shenzhen, the largest city, has the smallest four-industry concentration ratio of 35 percent, while Dongguan, the second smallest city, has the second smallest four-industry concentration ratio of 37 percent.

Similarly, again in contrast to the patterns noted above for market economies, there is no obvious correlation between industrial location patterns and city sizes. We compute the percentage of each city's total manufacturing output which is accounted for by each industry in that city. We then compute the correlations in these percentages across cities, the results being reported in Table 3. There appear to be two clusters of cities with similar industrial compositions. First, Fuzhou, Xiamen, Guangzhou, and to a lesser extent Dongguan have highly correlated industrial structures, the largest industry in all four cities being radio, television, and communication equipment; however, in spite of their similar industrial structures, these cities are of very different sizes. Guangzhou, the second largest of the eight cities, is 2-3 times larger than Fuzhou, Xiamen, and Dongguan. The second cluster of cities consists of Chongqing, Chengdu, and to a lesser extent Shenzhen, the major industries in these cities being transport equipment, industrial equipment, and iron and steel; however, these cities are again of very different sizes. Shenzhen, the largest city in the sample, is roughly twice the size of Chengdu and Chongqing. Quanzhou, the city with the smallest amount of manufacturing output, has the most unique industrial composition of the eight cities, its largest industries being textiles and food.

These findings are consistent with those of Henderson (1988) who also finds that China's cities do not correspond to the patterns observed in market-oriented economies. Thus, taken together, the evidence suggests that existing industrial location patterns in China are not those which one would expect if profit-maximizing firms had been able to choose their locations optimally over an extended period of time, thereby reducing the likelihood of omitted variables biasing the coefficients on measures of cities' industrial specialization and diversity.[9]

Turning to equation (7), data is needed for Z_i, the vector of variables which determine the effectiveness of firm i's R&D. Following Glaeser et al. (1992), the first element of Z_i is SPECIALIZATION, which is defined as:[10]

$$\text{SPECIALIZATION} = \frac{\text{output of i's industry in i's city/total output in i's city}}{\text{output of i's industry in 8 cities/total output in 8 cities}}$$

As indicated earlier, both the Porter and MAR theories state that as SPECIALIZATION rises spillovers rise which makes the R&D of firm i more productive; hence, if Porter and MAR are correct, the coefficient on SPECIALIZATION, ψ_1, should be positive.

Again following Glaeser et al. (1992), the second variable

[9] See the discussion in Section I.

[10] Glaeser et al. (1992) use employment rather than output in this expression.

of Z_i is DIVERSITY, which is defined to be the fraction of the city's output accounted for by the largest 5 industries in the city other than the industry to which firm i belongs. The higher the value of this variable, the less diversified is the city. As discussed earlier, Jacobs believes that more diversified cities are conducive to innovation, so if Jacobs is correct the coefficient on DIVERSITY, ψ_2, should be negative.

In order to examine whether the effects of SPECIALIZATION and DIVERSITY differ as the firm matures, we also interact these two variables with AGE, the age of the firm in 1992, and we include AGE on its own as well (ψ_3-ψ_5). As mentioned earlier, there is considerable interest in determining if the effects of SPECIALIZATION and DIVERSITY change as an industry matures (Glaeser et al. (1992), Henderson et al. (1995)).[11] Although firm age and industry maturity are not exactly the same thing, we would certainly expect that the average firm in a more mature industry would be older than the average firm in a less mature industry.

Both SPECIALIZATION and DIVERSITY are variables capturing the relative concentrations of industrial activity, but it is conceivable that what matters for firm i is the absolute magnitude of firm i's industry in the city in which the firm is operating. To take an extreme example, if only within-industry spillovers matter, then if firm i is the only firm in its

[11]See the discussion in Section I.

village there would be no spillovers to that firm. In contrast, another firm j in the same industry as firm i but located in a large city with many other firms in its industry would receive some spillovers from those firms. However, since firm i is the only firm in its village, the variable SPECIALIZATION would take on a value greater than 1 for this firm, while it would take on a value of less than 1 for firm j. In this scenario, the coefficient on SPECIALIZATION would take on a negative value even though spillovers are within-industry in nature. Hence, we think it is worthwhile to examine the effects of absolute industry size on R&D as well. Toward that end, the variable INDOUT is the total output of firm i's industry in firm i's city measured in 10 million yuan. If the absolute size of the industry raises spillovers, the coefficient on this variable, ψ_6, should be positive.

The second dimension of the three hypotheses concerning city types is the extent to which competition or monopoly power stimulates R&D. Our measure of the competition facing the firm is the variable ELASTIC, a dummy variable taking on the value of 1 if the firm believes the price elasticity of demand for its products is greater than or equal to two and 0 otherwise. As mentioned earlier, the firm's elasticity of demand appears to be a more precise measure of the degree of competition than that used in previous studies; however, there is a problem with using ELASTIC because the model presented in the previous section assumes that each firm's elasticity of demand is a function of its R&D; hence, we instrument for ELASTIC with NUMCOMP, the number of competitors which the firm believes it has in its city, a variable which is likely to be exogenous to the firm at this early point in the industrialization process, especially since existing location patterns are largely the result of past bureaucratic decisions. According to the theories of Porter and Jacobs, competition increases innovation, so the coefficient on ELASTIC, ψ_7, should be positive if Porter and Jacobs are correct. On the other hand, MAR predicts a negative coefficient on ELASTIC.

Several variables which control for the ownership structure of the firm are included in Z_i. The data enable us to distinguish between three types of firms: 1) state-owned enterprises, which are under the control of provinces, municipalities, or counties; 2) collectives, which are also owned by local governments but which typically enjoy greater decisionmaking freedom than the state-owned enterprises; and 3) joint ventures and other privately owned firms, which enjoy the greatest decisionmaking freedom.[12] We define JOINT to be a dummy variable which takes on the value of 1 if the firm is a joint venture or is privately owned and 0 otherwise. Similarly, the variable COLLECTIVE is a dummy variable which takes on the value of 1 if the firm is a collective and 0 otherwise. The effect of being a state-owned enterprise is subsumed in an intercept which is common to all three ownership types; hence, the coefficients

[12] See Jefferson et al. (1992).

on JOINT, ψ_8, and on COLLECTIVE, ψ_9, are the deviations in R&D of such ownership-types as compared to the state-owned enterprises.

We also control for city and industry characteristics by including city dummies (parameters ψ_{10}-ψ_{16}) and two-digit, industry dummies (parameters ψ_{17}-ψ_{23}). The seven industry dummies in conjunction with the intercept term, ψ_{24}, control for 8 different industry effects, the industries being food, textiles, paper and printing, chemicals, non-metallic minerals, basic metals, metal products and machinery, and other manufacturing industries.

As equation (7) indicates, all the variables in Z_i are multiplied by the firm's output at time zero, Q_{i0}, the latter being measured by each firm's nominal output in 1992 expressed in thousands of yuan. Because output is an endogenous variable, we instrument for it using two variables excluded from equation (7). The first, TRANSPORT, records each firm's evaluations of the impacts of transportation infrastructure on its growth, the responses taking on values from 1 to 7 with higher values indicating superior infrastructure. As a city's transportation infrastructure is exogenous to a firm and is unlikely to directly effect a firm's R&D, it appears to be a valid instrument for output.

Although TRANSPORT does significantly effect firm's output, much greater explanatory power comes from a second instrument, SIZE, which is defined as:

$$SIZE = LABOR_F(1.035)^{1992 - F}$$

where $LABOR_F$ is the number of employees, exclusive of R&D scientists, which the firm had in year F, where F takes on either the value of 1980 or the value of the initial year of start-up for the firm, whichever is greater. Data on LABOR are available for each firm for each year from 1980-1992. If the firm began prior to 1980, then F is equal to 1980.[13] For a firm which began in say, 1986, the first year of LABOR data would be for 1986, and F would take on the value of 1986. Multiplying $LABOR_F$ by 1.035 to the power of (1992 - F) simply adjusts the labor force in year F by the average growth in labor force from 1980-1992 for the firms in the data set.

Clearly, the validity of SIZE as an instrument for output depends on the exogeneity of $LABOR_F$. We believe a good case can be made for this. The mere fact that the error term in equation (7), ε_{i0}, occurs in 1992 and that F predates 1992 by as many as 13 years argues against correlation between $LABOR_F$ and ε_{i0}. Of course, if there is strong serial correlation in ε_{it} over time, one could still argue that $LABOR_F$ and ε_{i0} are correlated. However, this possibility is mitigated when one notes that China's economic reforms did not even begin until the late 1970s, so observers agree that a firm manager in 1980 would have had little ability to choose any of its inputs, especially its labor

[13] 49% of the firms in the sample began their operations after 1980.

force, in any sort of profit-maximizing fashion at this point in time.

But what about firms which began their production after 1980 when there was greater decision-making autonomy? Can we still treat $LABOR_F$ as independent of ε_{i0} for such firms? There is widespread consensus that China's labor markets remain the least reformed feature of the economy, making it very difficult for firms to dramatically alter the sizes of their workforces in a profit-maximizing fashion (Gordon and Li (1991); Byrd (1992); Jefferson and Rawski (1994)). Hence, even for a firm which began after 1980, the unreformed labor markets are still unlikely to permit feedback from ε_{i0} in 1992 to the firm's overall labor force size. Furthermore, it is doubtful that a firm would know much about ε_{i0} in its initial year of operation, given that it would have had no experience with R&D at that point.

Although we believe that $LABOR_F$ is unlikely to be correlated with the error term in equation (7), we test for the existence of correlation between our instruments and the error term by using a generalized method of moments specification test. Hansen (1982) and Newey (1985) have shown that the cross-product of the estimated residuals and the instruments, a product which should be close to zero if the instruments are valid, has a χ^2 distribution with the degrees of freedom equal to the number of overidentifying instruments. Low p-values for the computed χ^2 test statistic would reject the null hypothesis of no correlation between all the instruments and the residuals.

Our system is overidentified for two reasons. First, we have three variables which are excluded altogether from equation (7)--NUMCOMP, TRANSPORT, and SIZE--and only two endogenous regressors included in equation (7)--ELASTIC and Q. Second, although the exogenous variables in Z enter equation (7) only via their interaction with Q, we include both the exogenous variables in Z themselves as well as their interactions with SIZE in the list of instruments. For example, although the city dummies enter equation (7) only interactively with Q, both the city dummies and the interaction of these dummies with SIZE are included as instruments, giving us another source of overidentification. Thus, we have a total of 19 overidentifying instruments, giving us 19 degrees of freedom for the χ^2 test statistic.

Recall from equation (6) that we assume that a firm's expected growth in output is a function of its expectations concerning the output growth rate for its industry as a whole. We obtain information for this variable from the original survey in which each firm reports its expectations for the annual growth rate of markets in which the firm sells its primary products. It is reasonable to expect there to be a positive correlation between a firm's expectations concerning its own output growth and the growth of the industry as a whole. In other words, we would anticipate that λ is positive in equation (7).

Finally, in the absence of data on total R&D expenditures, the dependent variable is measured as the total number of R&D scientists and engineers employed by the firm. On average, firms in our sample devote 3.0 percent of the their labor force to R&D, a surprisingly high number when one considers that the fraction of manufacturing employment accounted for by R&D personnel is 4.3 percent in the United States and 3.4 percent in Japan.[14] As mentioned earlier, six of the eight cities used in this study are from China's technologically-dynamic, southeastern coast, so the sampled firms are in no way representative of the situation in China as a whole.

Table 4 presents the means and standard deviations of the variables.

IV. Estimation Procedures and Results

Equation (7) is estimated using weighted, nonlinear, two-stage least squares.[15] The instrument list is as follows: the exogenous variables in equation (7), TRANSPORT, NUMCOMP, and the interaction of all these variables with SIZE. Because λg_i in equation (7) must be less than 1 in order for equation (7) to be a solution to the firm's optimization problem, we constrain λg_i to be less than 1 for all observations. Table 5 provides the estimation results.

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[14]Computed using data from ILO (1995) and OECD (1995).

[15]The weights are the inverses of standard deviations of the form $\sigma = \beta_0 + \beta_1 SIZE + \beta_2 (SIZE)^2$, where the coefficients are estimated from the error terms of a preliminary, nonlinear, two-stage least squares regression.

Column 1 presents the results from a specification in which INDOUT and the interactions of AGE with SPECIALIZATION and DIVERSITY are suppressed. The coefficient on SPECIALIZATION is positive and significant, providing support for the MAR and Porter theories. Furthermore, the elasticity of R&D with respect to SPECIALIZATION is 2.49 when all variables are evaluated at their means. This high elasticity combined with the fact that a one standard deviation increase in SPECIALIZATION would amount to an increase in SPECIALIZATION of 75% indicate that the overall effect of industrial specialization on R&D appears to be rather strong.

The coefficient on DIVERSITY is also positive and statistically significant. Since the industrial diversity of a city falls as the variable DIVERSITY rises, these results indicate that diversity is not conducive to innovation, in contrast to the views of Jacobs. On the contrary, it appears that having a city which is focused on a small range of activities best promotes innovation. Furthermore, the elasticity of R&D with respect to (lack of) DIVERSITY is 9.31 when all variables are evaluated at their means. When one considers that a one standard deviation increase in (lack of) DIVERSITY constitutes a 15% rise in its value, it is clear that the stimulus to R&D of reducing industrial diversity is quite strong. In conjunction with the previously-mentioned, positive effects of industrial specialization, it appears that cities which concentrate their activities in a narrow range of endeavors are the most conducive to innovation, just as the theories of MAR and Porter suggest.

The coefficient on ELASTIC is positive and significant, indicating that competition is conducive to higher investments in R&D as suggested by Jacobs and Porter. Furthermore, the effect appears to be rather strong, for when the value of ELASTIC changes from 0 to 1 R&D rises by 154 units when all variables are evaluated at their means. Given that the mean level of R&D is roughly 30, competition appears to induce a rather substantial increase in investments in innovation. It must be noted, however, that only 18.7% of the firms have a value of 1 for the variable ELASTIC.

When we consider the performance of the theories in two dimensions, namely their views of the roles of both industrial specialization and of competition on innovation, the estimation results from column 1 provide clear support for the views of Porter. As Porter suggests, competition and industrial specialization are the most conducive to innovation.

Note that both collectives and joint ventures perform significantly less R&D than state-owned enterprises. This is consistent with the findings of a survey conducted by Jefferson et al. (1992) in which over 90% of firms reported that state-owned enterprises are the principal innovators in their product lines.

Note that the coefficient on AGE is significantly negative. We might expect age to have a positive effect on R&D: since older firms have more experience in conducting R&D their R&D should be more productive, causing them to spend more on R&D, all else equal. Indeed, as we shall see further below in a more general specification, this negative effect of AGE will become statistically insignificant and we will find a positive and significant influence of AGE on a firm's ability to learn from the spillovers of others.

Note also that, as we anticipated, when firm i expects its industry to grow rapidly it also expects its own output to grow rapidly, as indicated by the positive, significant estimate obtained for λ, the coefficient on expected market growth in the denominator of equation (7).

The last row of column 1 reports the p-value from the Hansen-Newey test for correlation between instruments and the error term of equation (7). The p-value of 0.58 clearly allows us to accept the null hypothesis that there is no correlation between the instruments and residuals, lending credence to the validity of our instruments.[16]

Column 2 explores the possibility that the absolute size of an industry in a city is more conducive to spillovers than relative size, the latter being captured by SPECIALIZATION. As mentioned earlier, to examine this question we include INDOUT, the total output of firm i's industry in its city, as a

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[16]Recall that SIZE is used because of the need to instrument for firms' output levels, Q_{i0}. The results indicate that SIZE and the other instruments are able to explain a high proportion of the variance in firms' output levels, as evidenced by the fact that the R^2 value from the first stage regression is .53 for Q_{i0}.

regressor. As we would expect, INDOUT is positively correlated with SPECIALIZATION and negatively correlated with DIVERSITY in the data. It is not surprising then that the inclusion of INDOUT lowers the coefficient on SPECIALIZATION and raises it on DIVERSITY. However, the coefficients on SPECIALIZATION and DIVERSITY remain positive and significant, while the coefficient on INDOUT is insignificant. In short, relative industrial concentration matters more than the absolute size of the industry.

Column 3 is identical to column 1 except that we now interact AGE with SPECIALIZATION and DIVERSITY. The coefficients on SPECIALIZATION and (lack of) DIVERSITY remain positive and significant, although the coefficients on these variables have dropped substantially from their levels in column 1.

Although the direct effect of AGE remains negative, it is now insignificant. However, the interaction of AGE with SPECIALIZATION is positive and statistically significant. As mentioned previously, the experience which comes with AGE appears to increase the ability of a firm to benefit from the spillovers of others, implying that the importance of specialization rises rather than declines as the firm matures. Since a mature industry is likely to have more older firms than a new industry would have, these results generally support the conclusions of Henderson et al. (1995) that the importance of SPECIALIZATION increases as an industry matures, i.e that within-industry knowledge spillovers can act as an "engine" of permanent, self-sustaining growth.

The coefficient on ELASTIC remains positive and significant, confirming that competition is conducive to innovation. The coefficients on JOINT and COLLECTIVE remain negative and significant, again suggesting that state-owned enterprises perform more R&D, all else equal. Finally, note that the p-value for the χ^2 test statistic is still 0.58, providing support for the validity of our instruments.

V. Concluding Remarks

The results provided here support the views of Porter: a specialized and competitive environment causes firms to innovate faster. Furthermore, it appears that the importance of specialization increases as a firm matures, casting a more favorable light than Glaeser et al. (1992) on the possibility that within-industry knowledge spillovers may be able to generate long-run growth.

These results also provide some support for the popular notion that free trade promotes growth in total factor productivity. To the extent that free trade causes greater industrial specialization and raises the level of competition, these results suggest that investments in innovation will be higher in an open than in a closed trading regime.

Finally, we caution the readers that our sample consists of relatively young firms. Although we find that the importance of within-industry spillovers rises with firm age, it is conceivable that spillovers from outside the industry could become more important at some future date, even for the older firms in our sample. Clearly, greater variation in firm age or longer time series data are needed in order to address these possibilities.

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TABLE 1

INDUSTRIAL BREAKDOWN
(Percentage in Parentheses)

Industries	Number of Firms in Sample	Total Industrial Output in 8 Cities in 10 million yuan
Food	20 (7.7)	609 (4.8)
Beverage	0 (0.0)	294 (2.3)
Tobacco	0 (0.0)	369 (2.9)
Animal Feeds	3 (1.1)	162 (1.3)
Textiles	30 (11.5)	739 (5.8)
Apparel	0 (0.0)	382 (3.0)
Leather/Fur	1 (0.4)	315 (2.5)
Wood	3 (1.1)	106 (0.8)
Furniture	0 (0.0)	75 (0.6)
Paper	7 (2.7)	242 (1.9)
Printing	7 (2.7)	225 (1.8)
Household Items	46 (17.6)	344 (2.7)
Petroleum	0 (0.0)	342 (2.7)
Basic Chemicals	14 (5.4)	813 (6.4)
Drugs	0 (0.0)	562 (4.4)
Resins	3 (1.1)	81 (0.6)
Rubber Products	7 (2.7)	221 (1.7)
Plastics	10 (3.8)	328 (2.6)
Non-Metallics	9 (3.4)	340 (2.7)
Iron and Steel	3 (1.1)	814 (6.4)
Non-Ferrous Metals	2 (0.8)	186 (1.5)
Metal Products	33 (12.6)	479 (3.7)
Machines: Non-elect	16 (6.1)	1,346 (10.5)
Transport Equipment	11 (4.2)	927 (7.2)
Machines: Electric	8 (3.1)	895 (7.0)
Communication Equip	19 (7.3)	1,527 (11.9)
Electric Appliances	9 (3.4)	65 (0.5)
Total	261 (100.0)	

17,787 (100.0)

TABLE 2

Manufacturing Output and Concentration in 1992

	Total Manufacturing Output in 10 Million Yuan	Percentage of Manufacturing Output Accounted for by the Four Largest Industries
Fuzhou	939	43
Xiamen	895	45
Quanzhou	129	50
Shenzhen	4,216	35
Guangzhou	2,251	59
Dongguan	613	37
Chengdu	1,644	48
Chongqing	2,099	56

<u>TABLE 3</u>

<u>Correlations in Cities' Industrial Composition</u>

	Fuzhou	Xiamen	Quanzhou	Shenzhen	Guangzhou	Dongguan	Chengdu	Chongqing
Fuzhou	1.00	0.78	0.13	0.27	0.80	0.65	0.32	0.22
Xiamen	0.78	1.00	0.29	0.20	0.79	0.57	0.17	0.16
Quanzhou	0.13	0.29	1.00	0.06	0.14	0.53	-0.01	0.07
Shenzhen	0.27	0.20	0.06	1.00	0.01	0.32	0.49	0.60
Guangzhou	0.80	0.79	0.14	0.01	1.00	0.56	0.17	0.07
Dongguan	0.65	0.57	0.53	0.32	0.56	1.00	0.15	0.22
Chengdu	0.32	0.17	-0.01	0.49	0.17	0.15	1.00	0.77
Chongqing	0.22	0.16	0.07	0.60	0.07	0.22	0.77	1.00

TABLE 4

MEANS AND STANDARD DEVIATIONS OF VARIABLES

VARIABLE	MEAN	STANDARD DEVIATION
I. ENDOGENOUS VARIABLES		
R (Number of R&D Personnel)	29.91	204.04
Q (Firm Output)	51.23	111.81
ELASTIC	18.7% have ELASTIC = 1	
II. INCLUDED EXOGENOUS VARIABLES		
SPECIALIZATION	1.22	0.91
DIVERSITY	0.52	0.08
INDOUT	67.80	82.74
JOINT	32.1% have JOINT = 1	
COLLECTIVE	25.6% have COLLECTIVE = 1	
AGE	18.07	14.79
g (Expected Market Growth)	0.18	0.13
City Dummies[1]:		
FUZHOU	16.0% have FUZHOU = 1	
XIAMEN	18.3% have XIAMEN = 1	
QUANZHOU	8.4% have QUANZHOU = 1	
SHENZHEN	8.0% have SHENZHEN = 1	
GUANGZHOU	14.1% have GUANGZHOU = 1	
DONGGUAN	6.5% have DONGGUAN = 1	
CHENGDU	15.3% have CHENGDU = 1	
Industry Dummies[2]:		
FOOD	8.8% have FOOD = 1	
TEXTILES	11.8% have TEXTILES = 1	
PAPER	5.7% have PAPER = 1	
CHEMICALS	13.0% have CHEMICALS = 1	
NONMETALS	3.4% have NONMETALS = 1	
METALS	1.9% have METALS = 1	
MACHINERY	36.6% have MACHINERY = 1	
III. EXCLUDED EXOGENOUS VARIABLES		
SIZE	827.26	2437.12
NUMCOMP	111.40	288.43
TRANSPORT	3.96	1.99

[1]The dummy for CHONGQING is omitted and is absorbed into the intercept.
[2]The dummy for "other manufacturing" industries is omitted and is absorbed into the intercept.

TABLE 5: ESTIMATION RESULTS WITH R&D AS DEPENDENT VARIABLE
(t-statistics in parenthesis)

VARIABLE (PARAMETER)	(1)	(2)	(3)

SPECIALIZATION*Q (ψ_1)	.656 (5.25)	.453 (2.38)	.344 (2.02)
DIVERSITY*Q (ψ_2)	5.75 (3.77)	8.10 (2.50)	3.96 (2.04)
AGE*Q (ψ_3)	-.039 (2.52)	-.038 (2.49)	-.046 (0.66)
AGE*SPECIALIZATION*Q (ψ_4)	---	---	.016 (2.24)
AGE*DIVERSITY*Q (ψ_5)	---	---	-.016 (0.13)
ELASTIC*Q (ψ_6)	1.65 (2.98)	1.66 (2.98)	1.39 (2.77)
INDOUT*Q (ψ_7)	---	4.88 x 10-6 (0.98)	---
JOINT*Q (ψ_8)	-1.54 (2.92)	-1.55 (2.93)	-1.36 (2.95)
COLLECTIVE*Q (ψ_9)	-1.65 (3.15)	-1.62 (2.95)	-1.40 (2.89)
FUZHOU*Q (ψ_{10})	-.187 (0.30)	.403 (0.52)	-.700 (1.06)
XIAMEN*Q (ψ_{11})	-.275 (0.46)	.135 (0.20)	-.863 (1.38)
QUANZHOU*Q (ψ_{12})	-.377 (0.53)	-.151 (0.21)	-1.04 (1.39)
SHENZHEN*Q (ψ_{13})	-2.06 (2.75)	-2.11 (2.63)	-2.47 (3.66)
GUANGZHOU*Q (ψ_{14})	.196 (0.32)	.182 (0.31)	-.508 (0.65)
DONGGUAN*Q (ψ_{15})	1.20 (0.78)	1.79 (1.11)	-.308 (0.21)
CHENGDU*Q (ψ_{16})	.941 (1.69)	1.11 (1.96)	.321 (0.54)
FOOD*Q (ψ_{17})	-.206 (0.94)	-.406 (1.33)	-.339 (1.44)
TEXTILES*Q (ψ_{18})	.656 (1.70)	.338 (0.70)	.490 (1.36)
PAPER*Q (ψ_{19})	3.29 (2.40)	3.35 (2.30)	2.91 (2.32)
CHEMICALS*Q (ψ_{20})	.193 (0.63)	-.147 (0.35)	-.065 (0.20)
NONMETALS*Q (ψ_{21})	.185 (0.21)	-.074 (0.08)	.248 (0.31)
METALS*Q (ψ_{22})	.243 (0.18)	-.146 (0.10)	-.143 (0.11)
MACHINERY*Q (ψ_{23})	.678 (2.63)	.466 (1.32)	.477 (1.60)
INTERCEPT*Q (ψ_{24})	-2.30 (1.87)	-3.73 (1.84)	-.396 (0.27)
g_i (λ)	2.50 (14.74)	2.42 (11.62)	2.49 (17.92)
	χ^2 Test Statistic (p value)		
INTERCEPT ($-\rho$)			
Adjusted R^2			

		-18.51
		(1.52)
		.421
	-11.59	17.17
	(0.99)	(0.58)
	.372	
-16.83	17.90	
(1.38)	(0.53)	
.383		
17.20		
(0.58)		

Innovation in Cities: Evidence from Chinese Firms

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Abstract: We examine the theories of Jacobs, Porter, and Marshall-Arrow-Romer concerning the economic environments most conducive to innovation. Employing data on relatively young firms from China's technologically-dynamic, coastal region, we find that cities which are industrially specialized and which have strong degrees of competition provide the greatest stimulus to firms' R&D expenditures, a set of findings consistent with the views of Porter. Furthermore, the benefits of specialization increase as firms mature, providing some support for the view that within-industry spillovers can be an "engine" of long-run growth.

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