Capital allocation, regional specialization, and spillover effects in China

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chapter

With a record-high economic growth rate and an important role in the world's economy, China has received ever-increasing research attention. An issue of great interest to researchers is the allocation of investment across regions in China. Some studies, such as Boyreau-Debray and Wei (2005), argue that capital allocation across Chinese provinces is becoming less efficient and that the direction of capital flows is from regions with high returns to those with low returns. In contrast, in a recent study, Bai, Hsieh, and Qian (2006) systematically investigate the aggregate returns to capital in China and find that they have remained high despite one of the highest investment rates in the world. Furthermore, they study the pattern of investment allocation across regions and find that the regional dispersion of returns to capital has decreased over time.

Another interesting issue is the degree of regional specialization in China. Has the degree of regional specialization increased or decreased as the economy has grown? What factors determine the trend of specialization across regions? In an earlier study, Young (2000) claims that regional economic structures in China are becoming increasingly similar, which implies a rise in local protectionism. In contrast, Naughton (2003) finds evidence consistent with increasing regional specialization in China using 1987 and 1992 input-output data. And Bai and others (2004) find that the degree of industrial agglomeration in China changed from a decline between 1985 and 1988 to an increase afterward during the sample period; they also find evidence consistent with both the market forces for specialization and the forces for local protectionism against specialization. In a recent paper, Bai, Tao, and Tong (2008) document a U-shape relationship between regional specialization and per capita gross domestic product (GDP) in China, which is consistent with the finding in Imbs and Wacziarg (2003), which investigates cross-country data.

A closely related issue concerns the agglomeration effect among neighboring firms. There are tradeoffs regarding the spatial concentration of industrial activities. On the one hand, agglomeration may induce regional disparity in economic development. On the other hand, it may allow firms in the same industry to benefit from the proximity of their peers. To better understand the tradeoffs regarding the spatial concentration of industrial activities, it is necessary to understand the agglomeration effect. There is a large literature on the agglomeration effect. However, depending on the methodology used, data sets employed, and countries studied, the empirical results vary greatly across empirical studies. Our knowledge about the agglomeration effect in China is even more inadequate. Most of the existing work in this regard focuses on the effect of the presence of foreign direct investment (FDI) on the performance of domestic firms. Such a focus is useful if we want to evaluate the effect of FDI, but it is not enough if we want to understand the tradeoffs involved with the spatial concentration of industrial activities.

In this chapter, we follow Bai, Hsieh, and Qian (2006) and study the allocation of investment across regions in China. We also extend the work of Bai, Tao, and Tong (2008) by using the most recent time series data from 1999 to 2003 to investigate recent trends in China's regional specialization. Our results confirm that the efficiency of China's resource allocation has been improving and that market forces have played an increasingly important role in China's economic development.

In addition, we study the spatial factors behind firm performance to contribute toward our knowledge about the tradeoffs regarding the spatial concentration of industrial activities. We consider the effect of the proximity of peers on firm performance and then explore how the effect depends on regional and industrial characteristics and whether firms of different ownership, different sizes, and so forth enjoy the agglomeration effect to the same degree.

The rest of the chapter is organized as follows. The following section addresses the allocation of investment across provinces and regional returns to capital in China. This is followed by an analysis of regional specialization and an examination of the spatial factors behind productivity growth among Chinese firms. A final section concludes.

Returns to capital across provinces

Bai, Hsieh, and Qian (2006) have studied returns to capital in China at length, especially aggregate returns to capital. They also provide some results regarding the allocation of investment as well as the returns to capital across provinces. Most results presented here closely follow their work.

Methodology and data

This section presents our methodology for estimating rates of return to capital; introduces data on aggregate output, capital stock, and share of capital; and reports our findings about rates of return to capital across Chinese provinces from 1978 to 2005. We pay particular attention to special features in China's national account statistics and recent revisions to the statistics.

Returns to capital. Following Bai, Hsieh, and Qian (2006), we calculate the real rate of return to capital $r(t)$ for each of China's 28 provinces for the years from 1978 to 2005 using the following equation:[1]

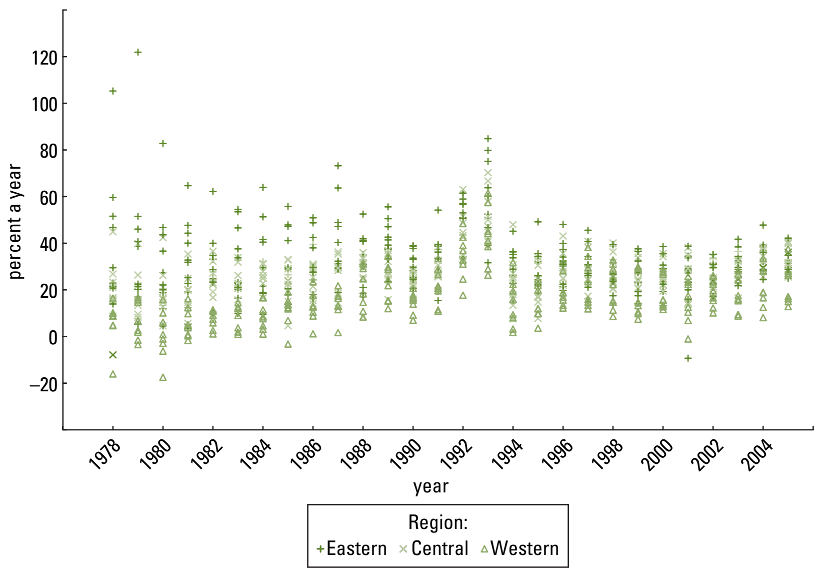
$$\begin{aligned} r(t) &= i(t) - \hat{P}_Y(t) \\ &= \frac{\alpha(t)}{P_K(t)K(t)/P_Y(t)Y(t)} \\ &\quad + \left(\hat{P}_K(t) - \hat{P}_Y(t)\right) - \delta(t). \qquad (17.1) \end{aligned}$$

Where i is the nominal rate of return, P_Y is the price of the output good, P_K is the price of capital, α is the share of payments to capital in GDP, δ is the depreciation rate of capital, $\hat{P}_Y$ and $\hat{P}_K$ are the percentage rates of change of the prices of the output good and capital, respectively, and $K(t)$ denotes the real value of the aggregate capital stock.

Aggregate output. To account for the possible bias in locally provided GDP, the National Bureau of Statistics adjusts the aggregate GDP based on nationwide economic censuses. Our estimation uses the revised national accounts data provided by the National Bureau of Statistics.

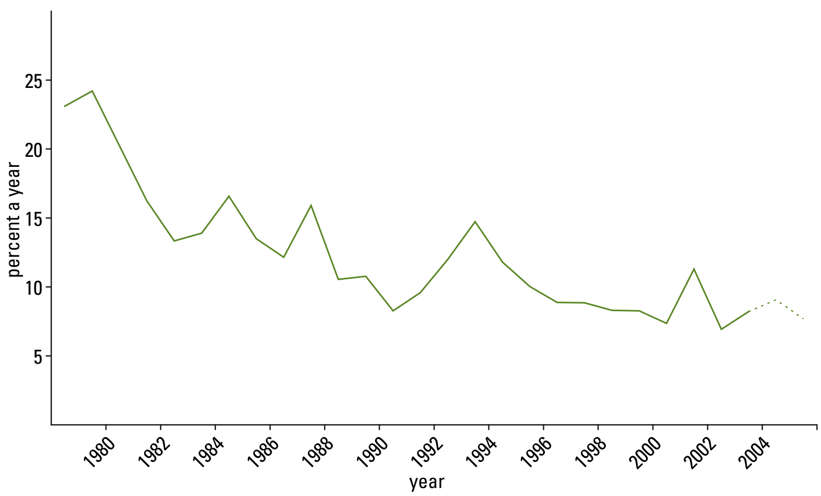
Capital stock. Compared with the widely used series for investment in fixed assets, the series for gross fixed capital formation is a more accurate measure of the change in China's reproducible capital stock. On the one hand, the series investment in fixed assets includes the value of purchased land and expenditure on used machinery and preexisting structures, which should not be included in investment data. On the other hand, the series may also understate aggregate investment, because it is based on survey data for large investment projects only. In contrast, in calculating gross fixed capital formation, the value of land sales and expenditures on used machinery and buildings are excluded from investment in fixed assets, and expenditures on small-scale investment projects are added. Therefore, we use this series to measure the capital stock and assume that

Figure 17.1 Returns to capital in China, by province, 1978–2005



Source: Bai, Hsieh, and Qian (2006).
Note: Each symbol represents the rate of return to capital of a province in the given year. Different symbols represent provinces from different regions (eastern, central, or western).

Figure 17.2 Standard deviation of returns to capital across provinces in China, 1978–2005[a]



Source: Bai, Hsieh, and Qian (2006).

the share of investment in structures and buildings and the share of investment in machinery and equipment are the same as those for investment in fixed assets.

For the investment price deflators, after 1990, the National Bureau of Statistics reports separate price indexes for investment in structures and buildings and for investment in machinery and equipment. For 1978–89, we use the deflator of value added in the construction industry for the price of structures and buildings and use the output price deflator of the domestic machinery and equipment industry for the price of machinery and equipment. Before 1978, we simply use the price of the two types of investment goods.

Then we employ the standard perpetual inventory approach to estimate the stock of the two types of capital. We initialize the capital stock in 1952 as the ratio of investment in 1953 (the first year for which investment data are available) to the sum of the average growth rate of investment in 1953–58 and the depreciation rate. The depreciation rate for structures and for machinery is assumed to be 8 and 24 percent, respectively.

Share of capital. We calculate the share of capital in total income from the residual of labor income. The National Bureau of Statistics provides annual data on the share of labor for each province and each sector, which can be used directly to estimate the share of capital for each province.

Returns to capital across regions

Figure 17.1 plots the returns to capital for each of China's 28 provinces from 1978 to 2005. Provinces are grouped into one of three regions—eastern, central, and western—as shown in the figure. One striking feature presented in the figure is the heterogeneity in the regional returns to capital. As clearly shown, the returns to capital are generally highest in the eastern region and lowest in the western region. However, the differences over time in the returns to capital across provinces are shrinking. The convergence of the regional returns to capital is also confirmed by figure 17.2, which shows that the standard deviation of the returns to capital across provinces is declining over the sample period.

Therefore, contrary to the findings of Boyreau-Debray and Wei (2005), the results presented here demonstrate that the dispersion in the returns to capital across regions in China has been shrinking and there is no evidence that capital flows from regions with higher returns to capital to those with lower returns. In other word, China's investment allocation across regions has become more efficient.

Regional specialization

This section considers how the degree of regional specialization depends on various factors. We use panel data across 31 Chinese regions to estimate the relationship between the degree of regional specialization and various factors.

Theory and hypotheses

There are a few theories about regional specialization, and each of them implies empirically testable hypotheses.

Stage of economic development and size of the economy. Using cross-country data, recent studies, such as Imbs and Wacziarg (2003), find that the relationship between the degree of regional specialization and per capita income is U shaped. They offer two possible explanations. First, consumers tend to demand a more diverse range of goods and services as their income rises, and this implies a diversification of economic activities if consumer demand cannot be met with imports from other countries due to high trading costs. Second, in the absence of perfect risk-sharing arrangements, it is risky for countries to specialize in producing a small set of goods and services, as predicted by the traditional theories of regional specialization (Kalemli-Ozcan, Sørensen, and Yosha 2003). To test whether this relationship holds for China's regional data, we include both per capita GDP and the square of per capita GDP in our regression.

Several studies, including Kalemli-Ozcan, Sørensen, and Yosha (2003), argue that larger regions tend to have lower levels of specialization due to more diversified demand and the exhaustion of scale economy. To capture this effect, we include a region's total population in the regression and expect it to have a negative effect on the degree of regional specialization.

Local protectionism. With fiscal decentralization, China's local governments have strong incentives to protect local firms and industries. However, the level and effectiveness of local protectionism depend on a number of factors. One is the size of local government expenditures relative to local GDP. Government spending is known for favoring local firms and industries. Furthermore, local governments with high ratios of expenditures to GDP are under financial pressure to practice local protectionism and obtain fiscal revenue to maintain their large public sectors. Thus regions with higher ratios of local government expenditures to GDP are expected to have more severe local protectionism. Local protectionism is a form of trade barrier. With higher trade barriers, the degree of regional specialization is lower.

The share of GDP from primary industries is another proxy for the level of local protectionism. Like other planned economies, China had national policies for developing manufacturing industries at the expense of primary industries—specifically, artificially suppressed prices for the output of primary industries but artificially inflated prices for the outputs of manufacturing industries—before its economic reform in 1979 (the so-called price-scissors problem; see, for example, Sah and Stiglitz 1984). In addition, due to central planning, those regions with high shares of GDP coming from primary industries may not have been the ones that further processed the outputs from primary industries and thus could not take full advantage of their resource endowments. Consequently, the price-scissors problem led to severe misalignment of economic interests among China's regions. Since China initiated its economic reform in 1979, the price of products from both primary industries and manufacturing industries has been increasingly determined by market forces, but it takes much longer to adjust the suboptimal geographic location of manufacturing activities. In general, manufacturing industries tend to have higher value added than primary industries do. As a result, it is expected that, in regions with higher shares of GDP from primary industries, local governments place more restrictions on the sale of the output from their primary industries to other regions, and consequently the degree of regional specialization is lower (Bhagwati 1988).

Market competition. Market competition greatly limits the effectiveness of local protectionist policies. To capture the domestic competition from firms in other regions, we construct a market potential measurement by using the weighted (weighted by the inverse of distance between different provinces) average of GDP from other provinces. Compared with domestic firms from other regions, foreign-invested firms and foreign imports pose a greater threat to local firms. We use two measurements to capture the effects of competition from foreign firms. One is the share of annual FDI inflows in a region to its GDP. The other is the distance of a region's capital to Hong Kong weighted by the percentage of China's exports going through Hong Kong. It is expected that the degree of regional specialization will be higher in regions with higher market potential or a higher ratio of FDI inflows to its GDP and in those regions closer to Hong Kong.

Methodology and data

This section defines the Hoover coefficient of localization and other variables and presents summary statistics.

Hoover coefficient of localization. To measure a region's degree of specialization in industrial production, we calculate the Hoover coefficient of localization (Hoover 1936) using output data for 32 two-digit industries in 31 Chinese regions over the period of 1999–2003. It is calculated based on the location quotient with respect to output, which is given by:

$$L_{ij} = \frac{OUTPUT_{ij} \,/\, OUTPUT_j}{OUTPUT_i \,/\, OUTPUT}, \qquad (17.2)$$

where $OUTPUT_{ij}$ is industry i's output in region j, $OUTPUT_j$ is total output in region j, $OUTPUT_i$ is industry i's total output, and $OUTPUT$ is total industrial output of China. If L_{ij} is larger than 1, then industry i has a higher percentage in region j than its share in the total industrial output of China and vice versa.

Analogous to the Gini coefficient for income distribution, to calculate the Hoover coefficient of localization, we first need to plot the localization curve for region j. Given the location quotient of region j for all industries, $i = 1,\ldots,l$, we rank industries by their location quotient in descending order and obtain a sequence of industries. Then the localization curve for region j can be plotted by calculating the cumulative percentage of output in region j (y axis) over the industries (x axis). The localization curve is the 45° line if every industry in a region contributes the same share of output as the whole country. And the localization curve is more concave if a region's economic activities are concentrated in only a few industries. Then the area between the 45° line and the localization curve divided by the entire triangular area in which the localization curve is contained defines the Hoover coefficient of localization, which is between 0 and 1. A higher Hoover coefficient corresponds to a higher degree of regional specialization.

Other variables. The following variables are used in this study:

- $HOOVER_{jt}$ is the Hoover coefficient of specialization of region j in year t;
- $rGOVT\_GDP_{jt}$ is the ratio of government expenditure to GDP of region j in year t;
- $\%PRIMARY_{jt}$ is the share of GDP contributed by primary industries of region j in year t;
- MP stands for market potential and is the weighted (weighted by the inverse of distance between different provinces) average of GDP from other provinces;
- $rFDI\_GDP_{jt}$ is the ratio of annual flow of FDI to GDP of region j in year t;
- $DIST\_HK_{jt}$ is the weighted distance to Hong Kong of region j in year t;
- $pcGDP_{jt}$ is GDP per capita of region j in year t;
- $pcGDP2_{jt}$ is the square of $pcGDP_{jt}$; and
- POP_{jt} is the population of region j in year t.

Summary statistics. Figure 17.3 plots the average Hoover coefficients across all regions from 1999 to 2003. The simple average for all regions was 0.541 in 1999 and 0.572 in 2000. The simple average Hoover coefficients remained at that level until 2001 and then jumped to 0.582 in 2003. The weighted (by regional industrial output) average across regions demonstrates a similar time trend, with each weighted average Hoover coefficient being about 0.04 larger than the corresponding simple average in each year. By using data over the 13-year period of 1985–97, Bai, Tao, and Tong (2008) show that China's regions have become more specialized in industrial production. Our result confirms that the degree of regional specialization in China has continued to grow in recent years. To see the significance of regional variations in the degree of specialization, we plot the time average of the Hoover coefficients of specialization for different regions. As shown in figure 17.4, Beijing has the highest degree of specialization, with a Hoover coefficient of 0.790, and Qinghai has the lowest degree of specialization, with a Hoover coefficient of 0.359.

The mean and rank of other variables across regions are presented in table 17.1.[2] The ratio of government expenditure to GDP has a mean of 0.151, with that for Tibet (0.521) being the highest and that for Hebei (0.078) being the lowest. And the share of GDP from primary industries ranges from 0.017 (Shanghai) to 0.374 (Hainan), with a mean of 0.176. Market potential, the share of FDI in GDP, and capacity-weighted average distance to Hong Kong range from 2,764.0 (Gansu) to 4,640.3 (Anhui), from 0 (Tibet) to 234.734 (Jiangsu), and from 0.0004 (Beijing) to 0.0139 (Ningxia), respectively. The means are 3,656.51, 35.792, and 0.0058, respectively. With per capita GDP of 38,019.6, Shanghai ranks first among all regions. Guizhou has the lowest per capita GDP, at 2,957.6. The mean per capita GDP is 9,584.4. With regard to population size, Henan ranks first with a population size of 0.944, and Tibet ranks the lowest with a population size of 0.026. Table 17.2 summarizes the pair-wise correlation of the key variables.

Regional specialization

To understand the underlying property and pattern of China's regional specialization, we estimate the following model:

$$\begin{aligned} LogitHOOVER_{jt} = {} & \beta_1 + \beta_2 GOVT\_GDP_{jt} \\ & + \beta_3 \%PRIMARY_{jt} \\ & + \beta_4 rFDI\_GDP_{jt} \\ & + \beta_5 pcGDP_{jt} \\ & + \beta_6 pcGDP2_{jt} \\ & + \beta_7 MP + \beta_8 DIST\_HK_{jt} \\ & + \beta_9 POP_{jt} + \gamma_t + \varepsilon_{jt}, \end{aligned} \tag{17.3}$$

Figure 17.3 Average of Hoover coefficients across regions in China, 1999–2003

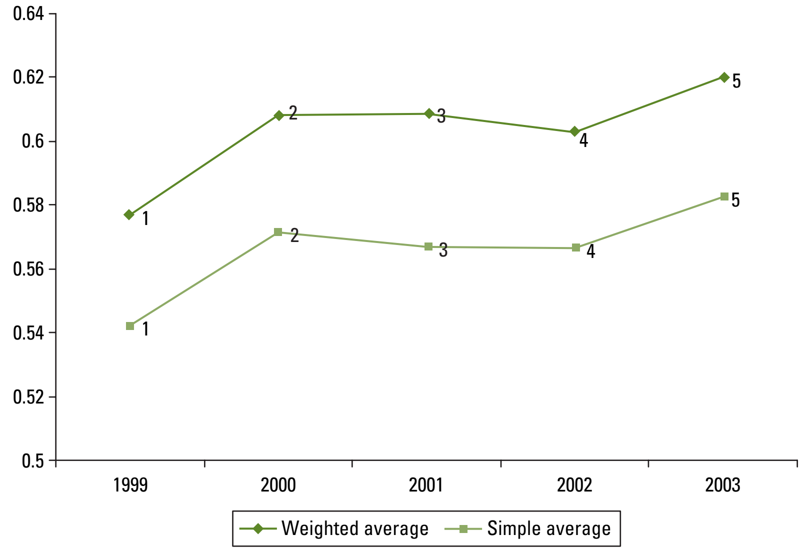
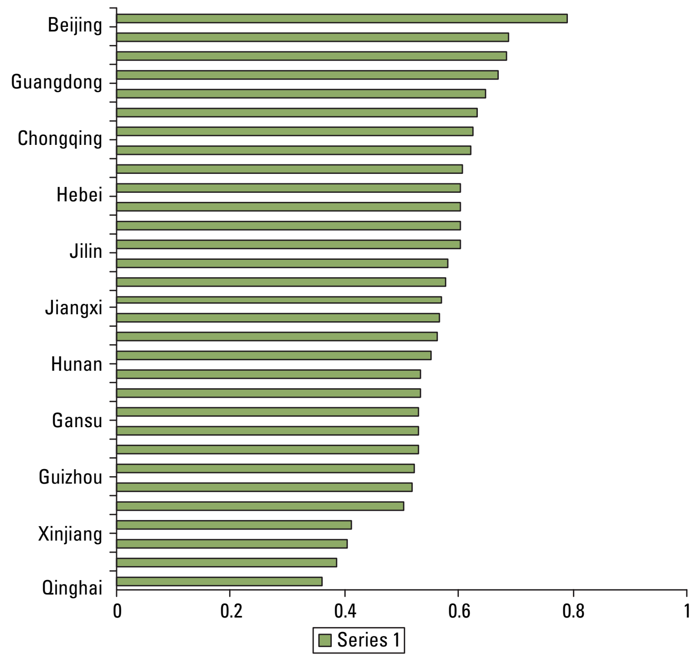


Figure 17.4 Average (across time) Hoover coefficient in China, by region



Source: Authors' calculations.
Note: Each bar refers to the Hoover coefficient of one province. There are 31 provinces, and the names along the vertical axis are the 11 regions that encompass the provinces.

where γ_t is the time-specific effect, and ε_{jt} is the error term, and

$$LogitHOOVER_{jt} = \ln\left(\frac{HOOVER_{jt}}{1 - HOOVER_{jt}}\right). \tag{17.4}$$

Table 17.1 Variable mean and rank

	Hoover		rGovt_GDP		%PRIMARY		rFDI_GDP		pcGDP		POP		MP		DIST_HK	
Region	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Beijing	0.79	1	0.18	8	0.03	30	67.23	7	25,667.8	2	0.11	26	3,716.4	15	0.0004	31
Hebei	0.6	10	0.08	31	0.16	18	14.91	16	8,517.0	11	0.67	5	3,727.1	14	0.0021	28
Shanghai	0.68	3	0.14	14	0.02	31	78.58	6	38,019.6	1	0.13	25	4,630.9	2	0.0038	23
Jiangsu	0.58	14	0.22	3	0.27	3	234.73	1	13,312.0	6	0.60	8	4,115.8	5	0.0048	18
Anhui	0.57	17	0.10	24	0.22	9	9.94	21	5,413.4	25	0.62	7	4,640.3	1	0.0066	13
Henan	0.52	26	0.08	28	0.22	11	8.94	23	6,053.6	18	0.94	1	3,850.5	12	0.0045	21
Hainan	0.6	11	0.12	18	0.37	1	83.79	5	7,306.2	15	0.08	28	4,037.3	7	0.0067	12
Guizhou	0.52	25	0.20	7	0.26	5	3.23	29	2,957.6	31	0.37	16	3,426.3	21	0.0096	4
Tibet	0.56	18	0.52	1	0.27	2	0.00	31	5,418.4	24	0.03	31	3,191.3	25	0.0043	22
Gansu	0.53	22	0.17	9	0.19	15	4.95	28	4,236.8	30	0.26	22	2,764.0	31	0.0071	10
Ningxia	0.51	27	0.22	4	0.17	17	8.93	24	5,429.4	23	0.06	29	3,151.6	26	0.0139	1
Mean	0.57	n.a.	0.15	n.a.	0.18	n.a.	35.79	n.a.	9,584.4	n.a.	0.40	n.a.	3,656.5	n.a.	0.0058	n.a.
Number of observations	155	n.a.	155	n.a.	155	n.a.	155	n.a.	155	n.a.	155	n.a.	155	n.a.	155	n.a.

Source: Authors' calculations.
n.a. Not applicable.

Table 17.2 Pair-wise correlations between main variables

Variable	Hoover	rGovt_GDP	%PRIMARY	rFDI_GDP	pcGDP	POP	MP	DIST_HK
Hoover	1							
rGovt_GDP	−0.19	1						
%PRIMARY	−0.34	0.23	1					
rFDI_GDP	0.43	−0.05	−0.08	1				
pcGDP	0.55	−0.11	−0.68	0.50	1			
POP	0.00	−0.41	0.08	0.06	−0.20	1		
MP	0.37	−0.36	−0.08	0.36	0.43	0.09	1	
DIST_HK	−0.45	0.06	0.41	−0.22	−0.44	0.00	−0.36	1

Source: Author's calculations.

The estimation results are presented in table 17.3.

The most interesting result is the U-shaped relationship between regional specialization and per capita GDP, as shown by the negatively significant (at the 5 percent level) estimated coefficient of per capita GDP and the positively significant (at the 5 percent level) estimated coefficient of per capita GDP square. Consistent with Bai, Tao, and Tong (2008), our result provides further evidence for the stage of development theory. Another variable that is also significant (at the 1 percent level) is market potential, which is positive and consistent with our expectation that more severe domestic market competition leads to a higher degree of regional specialization. However, the other variables, although statistically insignificant, do not appear to be consistent with the findings of Bai, Tao, and Tong (2008). In particular, the estimated coefficient for the ratio of local government expenditures to its GDP (*rGOVT_GDP*) is negative, as expected, and statistically insignificant. Thus a higher

Table 17.3 Estimation results with dependent variable: LogitHoover

Variable	Beta	t-value
GOVT_GDP	−4.04E-06	−1.3813
%PRIMARY	0.25707	1.416
rFDI_GDP	−0.000147	−0.73112
pcGDP	−1.54E-05	−2.2466**
pcGDP2	1.76E-10	2.0832**
MP	1.94E-05	3.0433***
DIST_HK	−1.49E-06	−1.2097
POP	−0.056435	−0.21264
Year dummies	Yes	
Number of observations	155	

Source: Authors' calculations.
*** Significant at 1 percent.
** Significant at 5 percent.

ratio of local government expenditures to its GDP implies a higher degree of local protection, although the relationship does not appear to be significant. Also consistent with our expectation, the coefficient for the weighted distance to Hong Kong is negative, implying that regions that are subject to stiffer competition from firms with foreign investment and foreign imports enjoy a higher degree of regional specialization. And the coefficient for a region's population (*POP*) is negative, as expected. As discussed in Bai, Tao, and Tong (2008), larger regions have lower degrees of specialization due to more diverse demand. At the same time, with the massive investments in infrastructure, the trading costs across regions are decreasing and so is the negative effect of the size of economy on regional specialization over time. Contrary to our expectation and the results in Bai, Tao, and Tong (2008), the coefficient for the share of GDP from primary industries (*%PRIMARY*) is positive, and the coefficient for the ratio of annual FDI flows of a region to its GDP (*rFDI_GDP*) is negative. As pointed out by Bai, Tao, and Tong (2008), the insignificance of the role of primary industries could be due to the fact that primary industries have become more market oriented and, consequently, the relationship between the size of the primary industries and local protection has been weakened. And the role of firms with foreign investment in the whole economy may be more complicated than we thought.

Spatial factors behind productivity growth

Externalities among firms form from two directions. One is localization economies, known as Marshall-Arrow-Romer (MAR) economies, where externalities come from other local firms in the same industry. The other is urbanization economies, known as Jacobs economies, where cross-fertilization from firms outside the same industry generates externalities. In this section, we use plant-level panel data to analyze agglomeration effects in Chinese firms. Our purpose is to identify the spatial factors behind the local productivity growth of Chinese firms. We follow the empirical framework in Combes (2000) and Cingano and Schivardi (2004), making some modifications to capture the special features of the Chinese economy.

Total factor productivity and underlying spatial factors

Due to data limitations, many empirical studies are based on employment growth; that is, they assume that growth in productivity is proportional to growth in employment. However, as discussed in Cingano and Schivardi (2004), this assumption is rather strong, and studies relying on this assumption might suffer from identification problems. Therefore, we follow Cingano and Schivardi (2004) and construct a measure of local total factor productivity (TFP) as the dependent variable. Specifically, we define TFP as Solow residual. To calculate TFP, we first estimate the following regression model using pooled panel data:

$$\ln(profit_{it}) = \alpha + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + \varepsilon_{it}. \qquad (17.5)$$

Then TFP can be obtained as

$$sTFP_{it} = \ln(profit_{it}) - \beta_1 \ln(K_{it}) - \beta_2 \ln(L_{it}). \qquad (17.6)$$

Intraindustry spillovers. We use two variables to capture the intraindustry spillover effects on the localization economies. One is N_{sr}, which is the number of firms in the same sector *s* and region *r*; the other is N_s, which is defined as the number of firms in the same sector *s* but not in the same region. As pointed out by Marshall (1920), externalities can occur through three mechanisms: knowledge spillovers, labor pooling, and learning. In this study, we do not intend to separate these mechanisms from each other; instead, we use N_{sr} to capture the effects of the spatial concentration of other firms from the same industry and use N_s to demonstrate whether these spillover effects operate locally or decay with distance.

Interindustry spillovers. To account for spillover effects from firms outside the same industry, we use two indicators to represent product variety. One is N_r, the number of firms in the same region r but not in the same sector. The other is a Hirschman-Herfindahl index, defined as

$$Variety_{r,s} = \sum_{j \neq s} \left(\frac{L_{r,j}}{L_r - L_{r,s}} \right)^2, \qquad (17.7)$$

where L is manufacturing employment.

Scale of the local economy. As suggested in Combes (2000), the scale of the local economy affects the intensity of spillover effects. On the one hand, the level and quality of spillover effects require a large enough number of firms. And large size of local markets helps to foster concentration of specialized inputs and to develop market demand. On the other hand, dense economic areas tend to have higher rent and higher input prices, as well as other negative effects such as congestion and pollution. We use the size of the regional population to represent the scale of the local economy.

Local competition. As discussed in Porter (1990), local competition fosters innovations and the adoption of new technology. However, if competition is too severe and the return to research and development (R&D) investment is too low, firms' motivations for R&D investment may be weakened. We define competition of sector s in region r as

$$Comp_{r,s} = \sum_{i \in r,s} \left(\frac{L_{r,s,i}}{L_{r,s}} \right)^2, \qquad (17.8)$$

where i is an index for the firm belonging to sector s and region i. L is labor employed.

Other variables. Given the special features of the Chinese economy, we also include the labor force employed at the firm level and its square, share of foreign capital, and share of state capital in the specification. Furthermore, to evaluate how the level of spillover effects differs across different types of firms, we also include interaction terms between intraindustry and interindustry spillover effects and firm assets, share of foreign capital, and share of state capital.

Summary statistics

Our estimated TFP ranges from 14.063 to 14.137, with a mean of 14.104. The average number of firms from the same sector in a region is 180.59, the minimum is 1, and the maximum is 726. For number of firms from the same sector but not in the same region, the mean, minimum, and maximum are 1,926.9, 3, and 4,193, respectively. And the number of firms in the same region and from the same sector ranges from 38 to 5,791, with a mean of 2,992.2. The various indexes have a mean, minimum, and maximum of 0.092, 0.046, and 0.618, respectively. The mean level of local competition is 0.111. The labor force employed ranges from 1 to 166,857 workers, with a mean of 483.937. And the mean share of foreign capital and state capital is 0.174 and 0.452, respectively. The average population size is 55.145 million, the minimum is 2.478 million, and the maximum is 95.847 million. And 64.24 percent of the firms are located in coastal areas. Finally, the firm assets range from Y 18,000 to Y 68.266 billion, with a mean of Y 126.28 million.

The final sample consists of 45,093 firms, which covers 30 regions and 37 industries, with a mean of 1,503.1 firms in a region.

Empirical Results

We estimate the following model:

$$\begin{aligned}
\ln(TFP)_{it} = {} & \alpha + \beta_1 N_{sr} + \beta_2 N_r + \beta_3 N_s \\
& + \beta_4 N_{sr} \times asset_{it} + \beta_5 N_s \\
& \times asset_{it} + \beta_6 N_r \times asset_{it} \\
& + \beta_7 N_{sr} \times foreign_{it} + \beta_8 N_s \\
& \times foreign_{it} + \beta_9 N_r \times foreign_{it} \\
& + \beta_{10} N_{sr} \times statet_{it} + \beta_{11} N_s \\
& \times state_{it} + \beta_{12} N_r \times state_{it} \\
& + \beta_{13} population_r + \beta_{14} Variety_{sr} \\
& + \beta_{15} competition_{sr} + \beta_{16} labor_{it} \\
& + \beta_{17} labor_{it}^{2} + \beta_{18} foreign_{it} \\
& + \beta_{19} state_{it} + dummies + \varepsilon_{it}, \qquad (17.9)
\end{aligned}$$

where four time dummies and a region dummy for coastal area are included to control for possible unobservable time and region effects that might confound with spatial spillover effects. The estimation results are presented in table 17.4.

The results show significant spillover effects, both intraindustry and interindustry, among Chinese firms. Specifically, the number of firms from the same sector in the same region has a positive effect on a firm's TFP growth; and smaller firms that have lower asset levels appear to benefit more than larger firms. Likewise, firms with a higher share of state capital tend to benefit more from the presence of other firms in the same sector and the same region, while the foreign capital share does not affect the magnitude of this type of spillover effects. As another indicator of intraindustry spillover effects, the number of firms from the same sector in other regions also shows a positive association with TFP growth. For this type of spillover effects, larger firms and firms with a higher share of foreign capital tend to benefit more, while firms with a higher share of state capital tend to benefit less. In addition, the TFP growth of a firm is positively correlated with the number of other firms in the same region, regardless of the sector, which indicates the presence of positive interindustry effects in a region. In particular, smaller firms, firms with a lower share of foreign capital, and firms with a lower share of state capital appear to enjoy more positive externalities from other firms in the same region but not in the same industry. At the same time, variety, another indicator of interindustry spillover effects, shows a negative effect, although it is significant only at the 10 percent level. The size of local economy, which is captured by population size, has a direct effect on TFP growth (at the 5 percent level). And local competition also shows a positively significant effect on TFP growth. As for the other variables, foreign capital share does not show any significant relationship with TFP growth, while state capital share shows a positive effect at the 5 percent level. Interestingly, the labor force employed by a firm exhibits a U-shaped relationship with TFP growth of the firm. Because the results are obtained after controlling for time and region unobservable effects, we believe they provide sensible estimates for spatial and other factors underlying TFP growth among Chinese firms.

Table 17.4 Estimation results with dependent variable ln*(TFP)*

Variable	Beta
Nsr	1.43E-06***
Nr	2.41E-06***
Ns	1.88E-07***
Nsr*asset	−4.48E-12***
Ns*asset	2.38E-13***
Nr*asset	−2.84E-14***
Nsr*foreign	1.75E-07
Ns*foreign	3.65E-07***
Nr*foreign	−3.06E-07***
Nsr*state	6.09E-07***
Ns*state	−9.68E-08***
Nr*state	−5.52E-08***
Population	0.0001083**
Variety	−0.0003379*
Competition	0.0007005***
Labor	−2.89E-06***
Labor^2	2.17E-11***
Foreign	−0.0001842
State	0.0001377**
Time dummies	Yes
Coast dummy	Yes
Number of observations	45,093

Source: Authors' calculations.
*** Significant at 1 percent.
** Significant at 5 percent.
* Significant at 10 percent.

Conclusions

Our study, along with recent studies including Bai, Hsieh, and Qian (2006) and Bai, Tao, and Tong (2008), shows that China, a country with a remarkable economic growth rate, has experienced improved resource allocation efficiency and exhibited an economic development trend consistent with that of other countries. Specifically, there is a convergence among returns to capital across regions in China, implying that investment has not been flowing to regions with lower returns to capital from those with higher returns. Consequently, China's allocation of investment across regions has not become more inefficient. The U-shaped relationship between regional specialization and per capita GDP demonstrates that, as an integrated part of the world's economy, China follows the same development trend for regional specialization as other countries. And fierce market competition has significantly limited the effectiveness of local governments' protectionist policies, which has helped to foster production specialization across provinces in China. These results suggest that market forces have played an increasingly dominant role in China's economy development.

The findings on agglomeration effects among Chinese firms show significant intraindustry and interindustry externalities. In particular, the number of firms from the same sector, either from the same region or from other regions, has a positive effect on a firm's TFP growth. And the TFP growth of a firm is positively correlated with the number of other firms in the same region, regardless of the sector. The strength of the spillover effect varies across different types of firms. Specifically, smaller firms and firms with a higher share of state capital benefit more from the presence of other firms in the same sector and in the same region. At the same time, larger firms, firms with a lower share of state capital, and firms with a higher share of foreign capital tend to benefit more from the presence of firms from the same sector but in other regions; however, larger firms and firms with a higher share of foreign capital appear to enjoy fewer externalities from other firms in other sectors and in the same region. Other factors, including product variety, local competition, scale of local markets, share of state capital, and labor force employed, also have a significant effect on TFP growth of Chinese firms.

Notes

Chong-En Bai is chair of the Economics Department, and Xu Lin is assistant professor in the Economics Department, both at Tsinghua University in Beijing. We thank Yukon Huang and other participants of the Tokyo workshop for their valuable comments and Jianhuan Xu for his excellent research assistance.

1. We include Hainan as part of Guangdong and Chongqing as part of Sichuan. Tibet is not included in our estimate of returns to capital due to data limitations.

2. To save space, we only report the mean and rank of the variables for some regions. The detailed information for all regions is available from the authors upon request.

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