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Sectoral Productivity and Regional Disparities in China, 1978–2006

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This paper examines labor productivity growth in the three main sectors in China in the context of regional convergence by employing a novel methodology and new sectoral data over the period 1978–2006. The results show that all sectors experienced major shifts in productivity but with different patterns. In agriculture and services, the uniform distribution has given way to a bimodal one. The secondary sector exhibits less polarization across regions despite higher mobility. Research and development (R&D) spending, human capital, and infrastructure are found to amplify regional divergence, while physical capital and foreign trade are identified as the key drivers of convergence.
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INTRODUCTION

Over the past three decades, the Chinese economy has undergone a remarkable structural transformation. In the late 1970s and early 1980s, fundamental reforms in agriculture fostered productivity gains that led to the reallocation of labor from the primary to the secondary sector, preparing the ground for rapid economic growth. In the 1980s and 1990s, the industrial sector experienced a significant boom as state-owned enterprises were restructured and corporatized, private manufacturing companies flourished, and joint ventures with foreign firms provided much-needed technology and know-how. As a result, over the past decade China has become the largest manufacturer in the world, enabling Chinese companies to expand their operations across the globe. At the same time, the service sector has grown in importance, but mostly at the expense of agriculture. The share of the primary sector in China's gross domestic product (GDP), which exceeded 30% in the early 1980s, gradually declined to a low of 10% in 2009. In contrast, the tertiary sector saw its share double from 21% in 1980 to 43% in 2009. The share of the secondary sector remained relatively stable at between 42% and 48% over the same period. At the sub-national level, structural change has occurred at different speeds, thereby contributing to regional disparities. For instance, the GDP share of agriculture in some interior provinces, such as Sichuan and Yunnan, still exceeds 15%, while it represents less than 5% in coastal provinces with high concentration of manufacturing, such as Guangdong and Zhejiang. The largely metropolitan regions of Beijing and Shanghai, on the other hand, rely mostly on the tertiary sector that claims a share of more than 60%.

This paper examines labor productivity growth in the three main sectors across Chinese provinces and its effect on regional disparities. The analysis of sectoral productivity over the past 30 years is crucial at a time when China is on the brink of another major structural transformation from an investment-driven economy with a predominant manufacturing sector to a consumption-driven economy, where the service sector plays a major role. The regional dimension of this process, which has been driven by labor shortages and increasing production costs in coastal provinces in recent years, is evident in the intensifying migration of manufacturing industries and foreign direct investment (FDI) to interior regions. Exploring the regional patterns in labor productivity growth in the three sectors offers important insights into the relationship between structural change and regional disparities that have been a key feature of China's transition to a global manufacturing power.

The goals of this paper are twofold. First, we examine the regional distribution of labor productivity in agriculture, industry, and services over the period 1978–2006. In particular, we model labor productivity growth as a discrete-time Markov process and estimate the transition probabilities across different ranges of sectoral output per worker relative to the mean. This approach allows us to detect and analyze convergence tendencies in each sector and forecast the evolution of the shape of the sectoral productivity distribution across regions over the long run. In addition, we test the robustness of the results in a continuous state space by using a non-parametric approach. Second, we employ a multinomial logit regression model to identify the determinants of labor productivity growth dynamics and their marginal effect in each sector. The sectoral regressions include a number of sector-specific variables that assess the contributions of capital, land, infrastructure, human capital, technology, environmental pollution, foreign trade, financial factors, and government policies.

The existing research on sectoral productivity at the regional level in China can be generally divided into three groups. The first uses a regression model of the production function to test for convergence in productivity across regions in agriculture (McErlean and Wu, 2003; Ito, 2010) or industry (Bai and Li, 2004; Jefferson *et al.*, 2008). The second group of studies decomposes productivity growth into efficiency and technological change, and then uses regional variations in the contributions of these components to identify convergence patterns (for agriculture: Chen and Song, 2008; Chen *et al.*, 2008; Li *et al.*, 2008; for industry: Marti *et al.*, 2011; for services: Qin, 2006). The third group conducts a comparative analysis across several sectors. For instance, Lu (2002) and Dekle and Vandenbroucke (2006) examine productivity growth and factor reallocation across various sectors but only at the national level.[1] Wu (1995) is the only comparative sectoral study that takes the regional dimension into account as it decomposes productivity growth and tests for regional convergence in agriculture, rural industry, and state industry over the period 1985–1991.

In contrast to previous studies, we employ a very different methodology with a focus on distribution dynamics that measures both productivity growth and convergence across regions in a given sector in terms of transition probabilities. The resulting analysis provides a far more detailed account because it relies on the entire distribution of sectoral output per worker across regions rather than just on the first two moments of the distribution. An additional advantage of the paper is that it utilizes a unique data set of capital stock by sector and region in China that accounts for province- and sector-specific depreciation rates and sector-specific deflators. Furthermore, our comparative analysis includes the service sector, which has received relatively little attention in the existing literature (Qin, 2006; Wu, 2007). Lastly, our sample covers all 31 Chinese provinces over almost 30 years, allowing us to investigate long-run patterns of convergence and structural transformation as well as their determinants.

Convergence in labor productivity across provinces is not necessarily the expected or desirable outcome. For instance, it is unlikely that labor productivity in the primary sector will ever converge across provinces, mainly

[1] Lu (2002) focuses on six sectors, including agriculture, two secondary, and three tertiary industries over the period 1986–2000. Dekle and Vandenbroucke (2006) study three sectors, including agriculture, private non-agriculture, and public non-agriculture over the years 1978–2003.

due to differences in geography and climate. However, regional divergence in the long run may create a number of policy challenges that would have to be addressed by the central government. More importantly, it is crucial to determine whether government policies and institutional factors impede convergence in productivity resulting from structural transformation, market forces, and globalization.

The rest of the paper is organized as follows. The next two sections describe the methodology and data, respectively. The subsequent section presents the results of the analysis and the last section concludes.

METHODOLOGY

A variety of methods have been used in the literature to study growth and convergence. Earlier studies tested for the existence of a negative relationship between the average income growth over a period of time and the initial level of income, which became known as β-convergence (Barro and Sala-i Martin, 1992). Other papers emphasized the importance of the decrease in dispersion of per-capita income across countries, termed σ-convergence (Friedman, 1992; Quah, 1993a). A third group of studies examined whether stochastic shocks that cause income differentials across countries are temporary in nature and would thus have no effect on convergence in the long run (Bernard and Durlauf, 1995). The presence of this stochastic convergence is usually investigated by testing for the stationarity of the income differential series using unit root tests. Further, the use of cointegration tests helps detect a common stochastic trend, which is interpreted as evidence of convergence.

In contrast to the aforementioned efforts, this paper employs a completely different non-parametric methodology. In a series of seminal papers, Quah (1993a, b; 1996a, b, c; 1997) criticized the standard econometric approach to income convergence, arguing that its focus on the first (β-convergence) and second (σ-convergence) moments of the income distribution describes the dynamics of a representative economy but fails to characterize the evolution of the entire income distribution over time. Instead, Quah used stochastic kernels to study both changes in the external shape of the entire distribution and intradistributional mobility, which allowed him to detect convergence clubs indicating the existence of multiple steady states. Following Quah (1996b, 1997), we use kernel density estimates to examine the shape of the sectoral income distribution across regions and employ transition probability functions to investigate distributional dynamics and intradistributional mobility in the three sectors.

Distribution dynamics and transition probabilities

The first step of the analysis involves estimating a probability density function of regional output per worker within a given sector using a kernel function. Let $X_1, \ldots \ldots, X_n$ be a sample of n independent and identically distributed observations on a random variable X. The density value $\hat{f}(x)$ at a given point x is estimated by the following kernel density estimator:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \tag{1}$$

where h denotes the bandwidth of the interval around x and K is the kernel function.[2] The kernel estimator assigns a weight to each observation in the interval around x with the weight being inversely proportional to the distance between the observation and x. The density estimate consists of the vertical sum of frequencies at each observation. The resulting smooth curve allows us to visualize the shape of the distribution of regional output per worker and detect the presence of 'convergence clubs' represented by modes.

Next, we study the dynamics of the distribution and intradistributional mobility of regions by estimating a transition probability matrix. Let Q_t denote the distribution of regional output per worker in a given sector at time t. The distribution at time $t+\tau$ is then described by:

$$Q_{t+\tau} = M \times Q_t \tag{2}$$

where M is a finite discrete Markov transition matrix that contains a complete description of the distributional dynamics as it maps Q_t into $Q_{t+\tau}$. The transition matrix is given by

$$M_{ij} = \begin{pmatrix} p_{ij} & \cdots & p_{iN} \\ \vdots & \ddots & \vdots \\ p_{Nj} & \cdots & p_{NN} \end{pmatrix} \tag{3}$$

where p_{ij} with $i, j = 1, .., N$ is the probability of a transition from an initial state i at time t to a state j at time $t+\tau$.[3] In other words, in the first row the initial state i remains constant across columns, while the final state j changes from 1 to N. In contrast, in the first column the final state j remains the same across rows, while the initial state i changes from 1 to N. The main diagonal of the matrix

[2] We use data-driven bandwidth selection and a Gaussian kernel.

[3] The word 'transition' in this context should not be confused with the transition from a planned to a market economy.

consists of the probabilities that an observation remains in the same state in t and $t+\tau$.

Assuming that the transition probabilities from t to $t+\tau$ are time-invariant and independent of any previous transitions, the evolution of intradistributional mobility can be studied by iterating equation 2 k times. As $k \to \infty$, the iteration yields

$$\lim_{k\to\infty} M_{ij}^{k} = \delta_j > 0, \ \sum \delta_j = 1 \tag{4}$$

The limiting probability distribution, δ_j, is the unconditional or ergodic distribution. [4] In other words, equation 4 describes the convergence to a steady-state distribution independent of the initial distribution. Accordingly, the ergodic distribution allows us to analyze the long-run tendencies of regional output per worker assuming that the observed dynamics continue to hold.

The transition probability matrix approach has two major drawbacks that might distort the distributional dynamics. First, it uses continuous data on regional output per worker to estimate a discrete model. Second, the discretization of the state space into states i and j, with $i, j = 1, \ldots \ \ldots, N$ is somewhat arbitrary. To avoid these potential issues and test for the robustness of the results, we focus – in the third step of our analysis – on transition probabilities in a continuous state space and, following Quah (1997), estimate a stochastic kernel that maps the distribution Q_t into $Q_{t+\tau}$ as follows:

$$Q_{t+\tau}(x_{t+\tau}) = \int g(x_{t+\tau} \mid x_t) Q_t(x_t) dx \tag{5}$$

where the conditional density function $g(x_{t+\tau} \mid x_t)$ describes the probability of the transition to a certain state in $t+\tau$ given the initial state in t. In line with Hyndman *et al.* (1996), the conditional density is estimated using a kernel estimator given by

$$\hat{g}(x_{t+\tau} \mid x_t) = \frac{\hat{z}(x_{t+\tau}, x_t)}{\hat{f}(x_t)} \tag{6}$$

where $\hat{f}(x_t)$ is the marginal density from equation 1 and $\hat{z}(x_{t+\tau}, x_t)$ is the joint density given by

$$\hat{z}(x_{t+\tau}, x_t) = \frac{1}{nhb} \sum_{i=1}^{n} K\left(\frac{x_{t+\tau} - X_{i,t+\tau}}{b}\right)\left(\frac{x_t - X_{it}}{h}\right) \tag{7}$$

with h and b denoting the bandwidth of the interval around x_t and $x_{t+\tau}$, respectively. The visual representation of the stochastic kernel is in the form of

[4] The ergodic distribution is unique if there is only one eigenvalue of M with modulus one.

a two-dimensional contour plot. As in a Markov transition matrix, a concentration of contour lines along the main diagonal indicates a lack of mobility across states.

Regression analysis

The distribution dynamics analysis focuses on the probability of moving across the state space of the transition matrix but does not explain the determinants of the transition process. Therefore, we relate the location in a given state of the Markov transition matrix to potential explanatory variables by employing a multinomial logit regression model. In particular, the dependent variable in the regression is categorical, with six possible outcomes defined as follows depending on where the output per worker of a given region i is located within the state space in year$t$ and year $t+\tau$:

$$y_{i,t+\tau} = \begin{cases} 1 & \text{if below the mean in } t \text{ and remains in the same state in } t+\tau \\ 2 & \text{if below the mean in } t \text{ but moves to a lower state in } t+\tau \\ 3 & \text{if below the mean in } t \text{ but moves to a higher state in } t+\tau \\ 4 & \text{if above the mean in } t \text{ and remains in the same state in } t+\tau \\ 5 & \text{if above the mean in } t \text{ but moves to a lower state in } t+\tau \\ 6 & \text{if above the mean in } t \text{ but moves to a higher state in } t+\tau \end{cases} \quad (8)$$

The vector of independent variables contains sector-specific regressors that are described in the next section. The coefficients in the model are estimated *via* maximum likelihood but are difficult to interpret in the current context as they represent logs of odds relative to a base category. Instead, we derive the marginal effect of a given regressor x on the probability of each category of the dependent variable as follows:

$$\frac{\partial P_m}{\partial x} = P_m(\beta_m - \sum_{q=1}^{6} P_q \beta_q) = P_m(\beta_m - \overline{\beta}) \quad (9)$$

where P_m is the probability of $y_{i,t+\tau} = m$, with $m = 1, \ldots, 6$ representing the categories of the dependent variable, while β_m is the estimated coefficient of regressor x for outcome m from the multinomial logit regression. The marginal effects are computed at the sample averages of the regressors.

DATA

The sample covers agriculture, industry, and services in all 31 Chinese provinces over the period 1978–2006. Data on output and labor by sector and province were collected from *China Compendium of Statistics, 1949–2008*

(National Bureau of Statistics, 2009). Output is converted in constant 1978 prices using the real growth rate and is expressed in per-worker terms. To facilitate the comparative analysis across sectors, we calculate the mean across provinces for each sector and express each regional output per worker as a percentage of the mean, which is set equal to 100.

The sectoral regressions contain two types of independent variables. The first consists of sector-specific variables that are either only relevant for a single sector or are reported by sector and region in the data sources. Data for the second type of variables are available by region but not by sector. Nevertheless, we include these regressors in the model because they represent important provincial characteristics that are relevant for all sectors, albeit to various degrees. The capital stock data set obtained from Wu (2009) is unique and, to the best of our knowledge, has not yet been used in previous research. Its major advantage is that province-level capital stock values are computed for each of the three main sectors using province-specific depreciation rates and sector-specific deflators. We include the capital–labor ratio in the regressions, which is computed by dividing the capital stock in each sector expressed in constant 1978 prices by the corresponding sector-specific labor.

For agriculture, we also estimate an alternative specification in which capital per worker is replaced by three components, including agricultural machinery measured by the power of machinery in kilowatts per agricultural worker, fertilizers expressed as chemical fertilizers in tons per hectare of sown area, and irrigation measured in hectares of irrigated area per hectare of sown area. Other input variables in the model specific to agriculture are land measured by sown area in hectares and electricity consumed in rural areas in terms of kilowatt hours per agricultural worker. Besides physical inputs, climate has also an effect on agricultural productivity and is represented in the model by average precipitation in millimeters and average temperature in degrees celsius. Moreover, rapid industrialization and weak regulation over the sample period have caused severe environmental degradation in China creating negative externalities. The potentially negative impact of industrial pollution on agricultural productivity enters the model in the form of industrial waste water discharge measured in tons per thousand yuan of provincial output. Although our choice is dictated mainly by data availability, water pollution does indeed hamper productivity in the primary sector *via* irrigation. Financial deepening has been shown to promote growth and therefore the role of financial inputs is controlled for by including agricultural loans in yuan per agricultural worker. Government policies in the sector are taken into account *via* public spending on agriculture expressed as a percentage of total provincial government spending. In addition, this variable reflects, in part, institutional changes as well. Since the 1980s, the tight government control over agriculture was gradually relaxed and replaced by agricultural taxes. In the early 2000s, these taxes were in turn eliminated as the government introduced direct subsidies to farmers.

In the regression for the industrial sector, the role of the government is assessed by including state ownership as a percent share of state-owned enterprises in gross industrial output, and budgetary revenue from the enterprise income tax per thousand yuan of gross industrial output. As in the case of agriculture, these variables provide insights into institutional changes as well. In the early 1980s, state-owned enterprises accounted for close to 80% of China's gross industrial output, but over the subsequent two decades this share has gradually dropped to below 40% in the mid-2000s. This was the result of deep institutional reforms in the secondary sector. Over the 1980s, the state-owned enterprises were transformed from government units that were allocated inputs and required to meet output targets to autonomous firms that responded to market prices and profits. In the 1990s this process was deepened as smaller state-owned enterprises were privatized or shut down while larger ones were restructured into joint-stock companies and corporations that paid corporate taxes and sought funding from banks (Li and Putterman, 2008). The last decade has seen these state-controlled corporations become global players who listed their shares on Chinese and foreign stock exchanges and acquired foreign companies.

Physical inputs besides capital per worker consist of electricity consumption in thousand kilowatt hours per industrial worker, and infrastructure in billion tons of freight per kilometer, while financial inputs enter the model in the form of industrial loans in million yuan per industrial enterprise and FDI in percent of provincial GDP.[5] The regression also contains the environmental pollution variable as it is likely to affect industrial productivity as well.

In the services sector, the government presence is controlled for by budgetary spending on culture, health, and other services as a percentage of total provincial spending. FDI is included in the equation because, as consumption has been increasing foreign service providers such as banks, retailers, and consultancies have entered the Chinese market and have contributed their expertise. Infrastructure and telecommunications measured by the number of mobile telephone subscribers per 1000 people enter the model because transportation, logistics, and telecommunications, besides being major service industries, also play a role in facilitating other services

[5] Although there is insufficient data on FDI by sector at the provincial level, industry was the recipient of approximately 60%–70% of FDI inflows in the late 1990s and the first half of the 2000s, while agriculture received less than 2%. For this reason, we exclude FDI from the regression for agriculture.

by increasing their productivity. Lastly, loans to enterprises in the tertiary sector in thousand yuan per sectoral worker take into account sector-specific financial inputs.

The variables that could not be broken down by sector at the provincial level include foreign trade measured by the sum of exports and imports as a share of provincial GDP, education in average years of schooling, and technological innovation expressed as spending on R&D as a share of provincial GDP. Being exposed to global competition and having access to skilled labor and advanced technologies benefit productivity across all three sectors. Average years of schooling were calculated as follows:

$$e_{it} = \frac{(6G_{1it} + 9G_{2it} + 12G_{3it} + 15.5G_{4it})}{G_{it}} \tag{10}$$

where G_{jit} is the number of individuals aged 6 and above in province i in year t, with j being the highest level of education attained ($j=1$ for primary, 2 for junior secondary, 3 for senior secondary, and 4 for tertiary level). The weights in the formula represent the length of the respective schooling cycles in years.[6] G_{it} is the total population aged 6 and above.[7]

The descriptive statistics of the major variables in Table 1 illustrate the large gap between low- and high-productivity provinces in China. [8] Labor productivity in above-average provinces is approximately twice as high across all three sectors. Below-average regions have only half as much capital per worker in agriculture and services as do their high-productivity counterparts but exhibit higher levels of industrial pollution. While government spending in agriculture and loans to industrial enterprises favor provinces with lower productivity, above-average regions have about three times higher levels of foreign trade and FDI. [9]

[6] The number of individuals with a tertiary education includes those with a junior college degree (15 years of schooling) and those with a university degree (16 years of schooling). Because the data did not us allow to separate these two groups, the average number of years was adopted as the length of the tertiary education.

[7] The data were obtained from the census in 1990 and 2000, the 1% population sample survey for 1995 and 2005, and from the 0.1% population sample survey for the remaining years of the sample.

[8] To save space, we exclude the descriptive statistics of some variables from Table 1 that are specific only to a single sector.

[9] Correlations among the explanatory variables were generally low and none exceeded 0.7. The only exceptions were electricity consumption in the primary sector, which was correlated with capital ($r=0.74$) and trade ($r=0.7$), and mobile telephones in the tertiary sector, which were correlated with capital ($r=0.7$) and government spending ($r=0.86$). Dropping these two variables from the respective sectoral regression models did not have an effect on the signs and significance levels of the remaining coefficients. The correlation matrices for each sector are available from the authors upon request.

Table 1: Descriptive statistics by sector and labor productivity levels, 1988–2006

	Agriculture		Industry		Services	
Productivity	Below mean	Above mean	Below mean	Above mean	Below mean	Above mean
Productivity (yuan/worker)	709.4 (273.1)	1639.7 (650.2)	8975.1 (5533.9)	15558.2 (12643.1)	3950.3 (1589.4)	7785.8 (4199.4)
Capital (yuan/worker)	1631.4 (1041.5)	3944.2 (3030.8)	30379.9 (23219.8)	43949.2 (30929.8)	16527.4 (10016.7)	33229.9 (20325.5)
Electricity (kWh/worker)	461.9 (646.9)	2147.2 (3207.4)	12613.9 (17568.5)	17415.6 (28966.3)	—	—
Loans (yuan/worker)	1892.8 (6673.8)	2874.1 (3417.5)	7.179 (6.556)	6.546 (6.316)	7418.8 (4505.1)	10857.9 (5105.4)
Gov. spending (% total exp.)	7.968 (2.789)	6.435 (2.937)	—	—	163.56 (135.80)	322.74 (335.88)
Pollution (ton/1000 yuan GDP)	5.995 (6.057)	4.278 (5.106)	5.866 (6.097)	4.519 (5.142)	—	—
Infrastructure (bn ton freight/km)	—	—	822.3 (794.4)	1406.4 (2253.8)	809.1 (783.42)	1459.6 (2302.5)
FDI (% of prov. GDP)	—	—	1.319 (1.451)	4.754 (4.688)	1.901 (2.405)	3.983 (4.670)
Education (years of schooling)	6.836 (0.961)	7.883 (1.103)	7.051 (0.845)	7.528 (1.429)	7.037 (0.789)	7.575 (1.492)
R&D (% of prov. GDP)	0.693 (0.531)	1.269 (1.784)	0.694 (0.540)	1.249 (1.761)	0.682 (0.505)	1.299 (1.809)
Trade (% of prov. GDP)	12.93 (17.93)	42.59 (41.23)	10.56 (7.90)	45.44 (42.93)	15.12 (17.50)	39.83 (43.95)

Note: The reported numbers are mean levels of the variables described in the 'Data' section with standard deviations in parenthesis.

RESULTS

Distributional analysis

The kernel density distributions of regional output per worker for the three sectors are shown in three-dimensional graphs in Figure 1. The corresponding two-dimensional graphs represent snapshots of the smoothed distribution in the initial and final years of the sample period. In all three sectors, the initial distribution in 1978 is very similar, with a strong concentration of the probability mass around the mean. In addition, all three graphs exhibit a far smaller but distinct mode at around twice the average level of output per

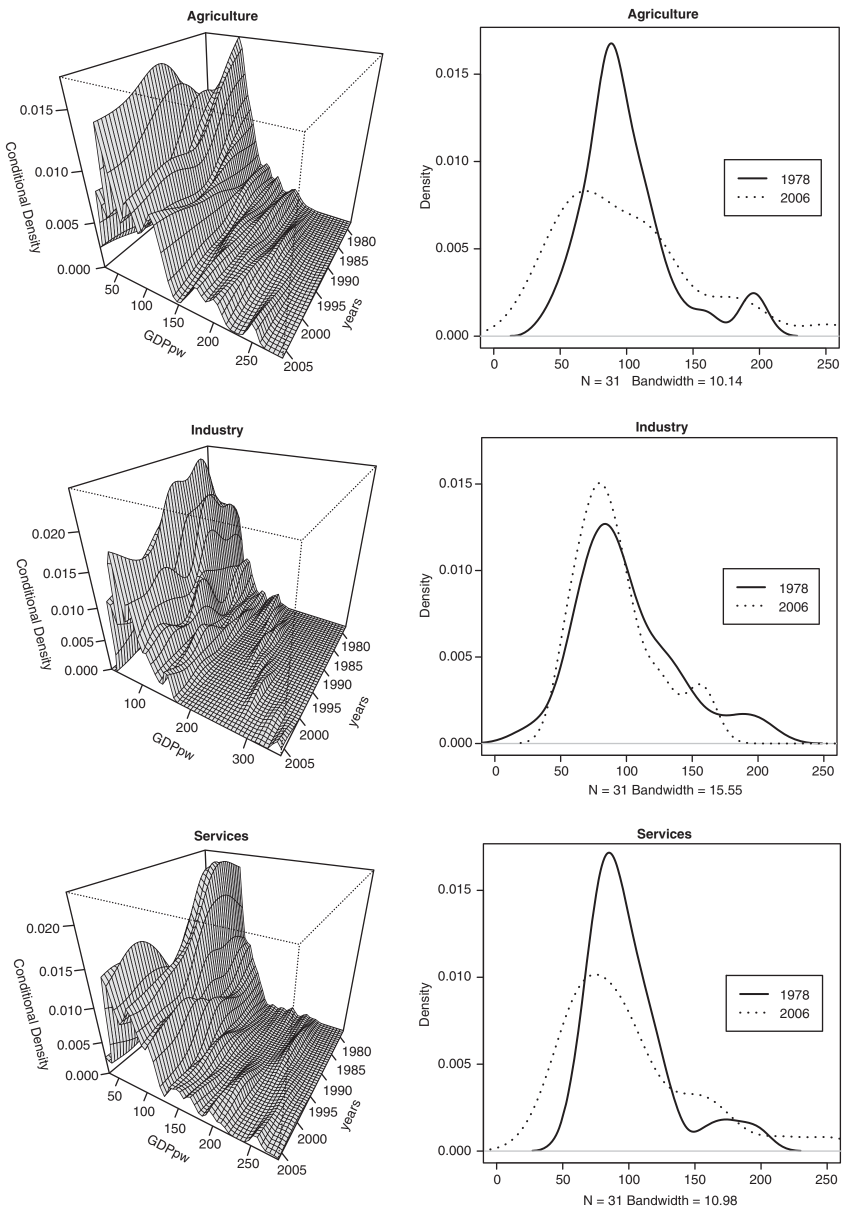

Figure 1: Kernel density distributions of regional output per worker by sector.

worker. But the evolution in the shape of the distribution over the sample period has taken a very different course across the three sectors.

In agriculture, the narrow peak around the mean has largely disappeared, suggesting divergence in output per worker. Part of the probability mass shifted towards lower output levels while the other part exhibited upward mobility that led to the dissipation of the single distinct mode at highest levels of labor productivity. The latter tendency indicates that many of the provinces at or below the mean converged towards higher levels of output per worker over the three decades of reform and opening.

The distributional dynamics in the industrial sector have been the opposite from agriculture. Between 1978 and 2006, the probability mass has moved towards the mean from both ends of the distribution resulting in an even higher concentration around the mean value. This is a sign of strong convergence within the distribution, which is further supported by the fact that the rich mode has also shifted closer to the mean. The boom in industrial productivity has enabled less productive regions to catch up with the more advanced ones in the secondary sector, while more productive provinces have failed to extend their lead relative to the mean.

In the tertiary sector, the divergence tendencies are much more pronounced than those in agriculture. The mode around the mean has become smaller but it has remained very prominent and has shifted to the left, suggesting that a large part of the probability mass has moved away from the mean. Similarly, some provinces have managed to converge towards higher levels of output per worker, amplifying the divergence within the distribution.

Transition probabilities

To gain a better understanding of the dynamics within the distribution, we employ Markov transition matrices, which report the probability of regions moving from one state associated with a certain level of output per worker to another over a period of 10 years. [10] For this purpose, we discretize the state space for each sector into six intervals chosen in such a way that each interval contains an approximately equal number of transitions. The corresponding transition matrices are presented in Table 2. The value range for the initial state is given in each row, while the ranges for the states to which a region has transitioned after 10 years are reported in the columns.

In agriculture, persistence at both ends of the distribution is similar with a probability of regions moving away from their initial state estimated at 20% or less. In contrast, there is very high mobility in the middle of the distribution. Regions with productivity levels firmly below the mean exhibit a strong

[10] We opt for the 10-year periods because annual transitions are too short to result in any significant movements across the six states despite the rapid growth of many regions in the sample. In addition, 10-year transitions control for the effect of short-run fluctuations that are likely to occur.

Table 2: Transition matrices and ergodic distributions of output per worker, 1978–2006 (10-year transitions)

Agriculture							
State	[26; 62)	[62; 75)	[75; 89)	[89; 107)	[107; 140)	[140; 286]	n
[26; 62)	0.82	0.18	0	0	0	0	98
[62; 75)	0.36	0.49	0.13	0.02	0	0	98
[75; 89)	0.12	0.38	0.17	0.21	0.11	0	98
[89; 107)	0.06	0.05	0.26	0.27	0.31	0.06	98
[107; 140)	0	0	0.08	0.23	0.44	0.24	98
[140; 286]	0	0	0	0.02	0.20	0.78	98
Ergodic	0.51	0.23	0.06	0.04	0.07	0.09	589
Industry							
State	[28; 75)	[75; 83)	[83; 92)	[92; 103)	[103; 121)	[121; 353]	n
[28; 75)	0.43	0.21	0.12	0.07	0.10	0.06	98
[75; 83)	0.44	0.21	0.17	0.06	0.07	0.04	98
[83; 92)	0.31	0.24	0.11	0.16	0.08	0.09	98
[92; 103)	0.14	0.11	0.13	0.17	0.28	0.16	98
[103; 121)	0.05	0.18	0.13	0.28	0.17	0.18	98
[121; 353]	0.01	0.03	0.02	0.17	0.19	0.57	98
Ergodic	0.24	0.16	0.11	0.15	0.15	0.19	589
Services							
State	[32; 75)	[75; 84)	[84; 93)	[93; 102)	[102; 124)	[124; 283]	n
[32; 75)	0.76	0.17	0.05	0.02	0	0	98
[75; 84)	0.45	0.15	0.22	0.09	0.07	0.01	98
[84; 93)	0.30	0.12	0.24	0.18	0.11	0.04	98
[93; 102)	0.11	0.23	0.11	0.13	0.26	0.15	98
[102; 124)	0.07	0.03	0.11	0.16	0.36	0.27	98
[124; 283]	0.04	0.02	0	0.07	0.20	0.66	98
Ergodic	0.46	0.13	0.10	0.08	0.10	0.13	589

convergence towards the bottom of the distribution and away from the mean. Those at or above the mean have an approximately identical chance of moving towards higher or lower levels of labor productivity. The estimated ergodic distribution, shown at the bottom of the matrix, suggests that if these convergence patterns would remain constant in the long run, the distribution would become bimodal. In particular, two different but distinct convergence clubs would emerge at each end of the distribution. The majority of provinces would end up at the lower levels of agricultural productivity, while the most productive provinces would create an exclusive group.

In industry, the mobility across states is remarkable, signifying the rapid changes in sectoral productivity over the sample period. For instance, a region with an initial productivity level of less than 75% of the mean has a 6% chance of achieving productivity of between 1.2 and 3.5 times the mean value within a decade. At the other extreme, a region with the highest labor productivity in the secondary sector can drop to the bottom of the distribution with a probability of 1%. As in the primary sector, persistence is higher at both ends of the distribution as compared to the middle, but the chance of the least productive regions moving up exceeds 50%, while mobility at the very top is lower. Regions at or below the mean have a stronger convergence tendency towards lower productivity levels. Provinces with above-mean productivity have a higher probability of shifting towards the mean than away from it. Accordingly, the resulting ergodic distribution exhibits far less polarization than in the primary sector. The modes at both extremes of the distribution are detectable but not very pronounced while the middle of the distribution is almost uniformly distributed.

Despite higher mobility across states, the dynamics in the tertiary industry show more similarities with the primary than with the secondary sector. The persistence at both ends of the distribution is high, making it almost impossible for a low-productivity region to reach the mean level. The thinning out in the middle of the distribution underlines the divergence away from the mean, which is more obvious for productivity levels below the mean. This is reflected in the bimodal ergodic distribution that has a larger mode at the bottom and a smaller one at the top of the distribution, indicating that polarization in service productivity across regions is likely to continue if the convergence patterns over the last three decades remain in place. [11]

Stochastic kernels

In view of the continuous nature of output data and the arbitrary way of discretizing the state space, the robustness of the results is tested by estimating transition probabilities in a continuous state space. The resulting stochastic kernels are shown in Figure 2. The vertical dimension of the three-dimensional graphs measures the conditional probability of moving to a certain productivity level given an initial state of labor productivity a decade ago. As with the Markov transition matrix, peaks along the main diagonal indicate high persistence and lack of intradistributional mobility, while peaks off the diagonal denote a high probability of convergence or divergence. Figure 2 also includes contour plots that provide a two-dimensional view of the distributions, where contours represent points of equal frequency.

The graphs largely confirm the results from the section ‘Transition probabilities’, but they also provide more detailed insights into the movements

[11] We thank the anonymous referee who pointed out that there is a statistical break in the employment series in 1990 due to changes in the measurement methodology. Accordingly, we conducted the analysis for the subperiod 1996–2008 but found that the qualitative conclusions about patterns and distributional dynamics remain largely robust. The results of this robustness test are available from the authors upon request.

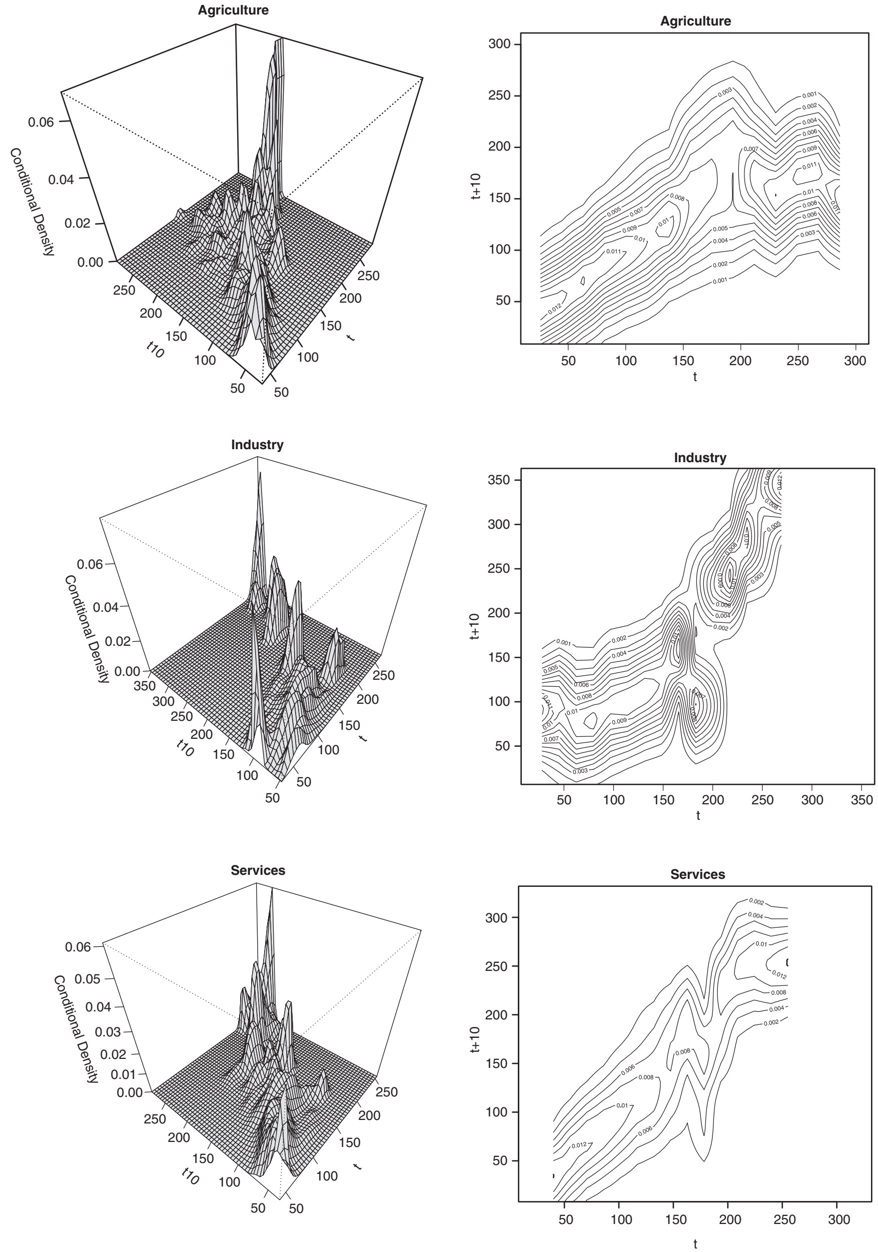

Figure 2: Stochastic kernels of the labor productivity distribution by sector.

at higher productivity levels that were obscured by the discretization of the state space. In agriculture and services, the gap between the lower and higher modes is clearly visible at or slightly above the mean. In contrast, the space between the two extreme modes in the secondary sector is occupied by a myriad of other modes that lessen the polarization of the distribution. Another interesting difference is that the mode at the highest levels of productivity is located below the diagonal for agriculture, but above it for industry. This illustrates the fact that in the primary sector there is convergence within the regional club at high levels of output per worker, whereas in the secondary industry part of these regions moves closer to the mean while another group diverges towards even higher productivity levels.

The determinants of distribution dynamics

The results from the multinomial regressions are presented in Tables 3–6. The dependent variable is categorical with six possible states described in the 'Regression analysis' section. The analysis focuses mostly on those regions that

Table 3: Marginal effects in the multinomial regression for agriculture (1)

	Below/ same	Below/ lower	Below/ higher	Above/ same	Above/ lower	Above/ higher
Capital	0.0001	0.0004**	−0.0007**	0.0001	−0.0003*	0.0003*
	(0.0002)	(0.0002)	(0.0003)	(0.0000)	(0.0002)	(0.0002)
Land	−1.0009**	−1.0431***	0.0376	1.0746***	0.5058***	0.4260**
	(0.2418)	(0.2471)	(0.2892)	(0.2047)	(0.1600)	(0.1735)
Precipitation	−0.0004	−0.0033***	0.0021**	0.0013*	0.0004	−0.0008
	(0.0004)	(0.0008)	(0.0008)	(0.0007)	(0.0004)	(0.0007)
Pollution	−0.0050	0.0170***	−0.0174**	0.0026	−0.0011	0.0038
	(0.0032)	(0.0051)	(0.0074)	(0.0055)	(0.0037)	(0.0052)
Electricity	−0.0009*	−0.0001**	0.0001**	0.0008**	0.0006**	−0.0003
	(0.0005)	(0.0000)	(0.0000)	(0.0003)	(0.0002)	(0.0003)
Loans	0.0003***	0.0004***	0.0000	−0.0005	−0.0007***	−0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.1337)	(0.0001)	(0.0002)
Government spending	0.0268***	0.0219**	−0.0139	−0.0231**	−0.0231***	0.0114
	(0.0082)	(0.0100)	(0.0139)	(0.0115)	(0.0077)	(0.0112)
Education	0.0388**	0.0409	−0.0452	0.0803*	−0.0700**	−0.0448
	(0.0186)	(0.0264)	(0.0476)	(0.0479)	(0.0295)	(0.0419)
R&D	−0.0394	0.0027	−0.0666	0.0233	0.0247	0.0553**
	(0.0252)	(0.0313)	(0.0612)	(0.0283)	(0.0193)	(0.0254)
Trade	−0.0084***	−0.0064**	0.0048***	0.0032**	0.0020**	0.0049***
	(0.0024)	(0.0409)	(0.0019)	(0.0013)	(0.0008)	(0.0012))
Log likel.		−658.07		Observations		589
Chi-square		697.77***		McFadden pseudoR^2		0.347

*** p<0.01; ** p<0.05; * p<0.10.
Note: The marginal effects are the derivatives of the probabilities from the logit regression with respect to the regressors. Standard errors are in parenthesis.

Table 4: Marginal effects in the multinomial regression for agriculture (2)

	Below/ same	Below/ lower	Below/ higher	Above/ same	Above/ lower	Above/ higher
Machinery	0.1163***	0.1210***	−0.0048	−0.108***	−0.1291**	0.0043
	(0.0338)	(0.0394)	(0.0529)	(0.0386)	(0.0526)	(0.0260)
Irrigation	−0.0086***	−0.0040**	−0.0025	0.0071**	0.0004	0.0076***
	(0.003)	(0.0027)	(0.0045)	(0.0028)	(0.0012)	(0.0019)
Fertilizer	−0.0666	0.3574**	−1.386***	0.5275***	0.2348**	0.3332***
	(0.0971)	(0.1493)	(0.2885)	(0.1874)	(0.1170)	(0.1259)
Land	−0.9903***	−1.189***	0.1880	1.329***	0.1858	0.4767**
	(0.3221)	(0.3286)	(0.3539)	(0.2578)	(0.1175)	(0.1856)
Temperature	−0.0093*	−0.0254***	0.0484***	−0.0057	−0.0213**	0.0132*
	(0.0051)	(0.0095)	(0.0115)	(0.0103)	(0.0084)	(0.0073)
Pollution	−0.0035	0.0127***	−0.023***	0.0078	0.0014	0.0048
	(0.0025)	(0.0048)	(0.0081)	(0.0071)	(0.0029)	(0.0042)
Electricity	−0.0001***	−0.0002**	0.0001*	0.0002***	0.0001**	−0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
Loans	0.0001*	0.0003*	−0.0001	0.0000	−0.0001***	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Government spending	0.0192**	0.0365***	−0.0178	−0.0368**	−0.0204**	0.0192*
	(0.0076)	(0.0124)	(0.0164)	(0.0146)	(0.0081)	(0.0114)
Education	0.0136	0.0076	−0.0547	0.1074*	−0.0259	−0.0480
	(0.0171)	(0.0314)	(0.0627)	(0.0619)	(0.0245)	(0.0410)
R&D	−0.0193	0.0013	−0.0371	0.0380	−0.0176	0.0347*
	(0.0216)	(0.0289)	(0.0533)	(0.0347)	(0.0341)	(0.0200)
Trade	−0.0026*	−0.0090***	0.0101***	−0.0004**	0.0004	0.0016
	(0.0015)	(0.0034)	(0.0024)	(0.0019)	(0.0008)	(0.0010)
Log likel.		−587.09		Observations		589
Chi-square		839.73***		McFadden pseudo R^2		0.417

*** $p<0.01$; ** $p<0.05$; * $p<0.10$.
Note: The marginal effects are the derivatives of the probabilities from the logit regression with respect to the regressors. Standard errors are in parenthesis.

move either towards or away from the mean since they reveal the patterns of distribution dynamics. Accordingly, a variable contributes to regional convergence if the coefficients for below-average regions that move to lower levels and above-average regions that move to higher levels of productivity carry a negative sign. Similarly, an indication of convergence tendencies is a positive sign of the coefficients for below-average regions that move upward and for above-average regions that move downward. [12]

[12] Growth regressions are likely to suffer from endogeneity because of reverse causality between growth and explanatory variables, such as capital accumulation, FDI, electricity consumption, and R&D spending. Although data limitations prevent us from addressing this issue econometrically, the categorical nature of the dependent variable in our specification mitigates the problem to a certain extent.

Table 5: Marginal effects in the multinomial regression for industry

	Below/ same	Below/ lower	Below/ higher	Above/ same	Above/ lower	Above/ higher
Capital	−0.0006	−0.0025**	0.0003	0.001	0.0019	−0.0000
	(0.001)	(0.0011)	(0.0014)	(0.0007)	(0.0012)	(0.0002)
State-owned	0.0029**	−0.0002	−0.0032*	−0.0021**	0.0034**	−0.0006
	(0.0014)	(0.0011)	(0.0019)	(0.0009)	(0.0017)	(0.0004)
Electricity	−0.0077***	0.0007	0.0015	0.0033***	0.0002	0.0001
	(0.0026)	(0.0013)	(0.002)	(0.0008)	(0.0012)	(0.0006)
Tax	−0.0053***	−0.003*	0.0052***	0.001**	0.0022	0.0001
	(0.0021)	(0.0016)	(0.0018)	(0.0004)	(0.0015)	(0.0001)
Loans	0.0016	−0.0004	0.0151**	−0.0043	−0.0123**	−0.001
	(0.0036)	(0.0033)	(0.0062)	(0.0038)	(0.0055)	(0.0012)
Pollution	−0.007**	−0.0117***	0.0156***	0.0072**	−0.0032	−0.0008
	(0.0036)	(0.0035)	(0.0056)	(0.0029)	(0.0051)	(0.0015)
Infrastructure	−0.0000	0.0004*	−0.0001**	0.0000	0.0001***	0.0000
	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FDI	0.001	−0.0794***	0.0638***	0.0172***	−0.0051	0.0025
	(0.0069)	(0.0105)	(0.012)	(0.0048)	(0.0121)	(0.0018)
Education	−0.0054	−0.0176	−0.0149	0.0369*	−0.0074	0.0083
	(0.0187)	(0.0192)	(0.0355)	(0.019)	(0.0308)	(0.0063)
R&D	0.0014	−0.0034	−0.0136	0.0958***	−0.0886*	0.0084
	(0.0225)	(0.0274)	(0.050)	(0.0245)	(0.0497)	(0.007)
Trade	−0.0042***	−0.0083***	0.0034**	0.005***	0.0036***	0.0005*
	(0.0011)	(0.0016)	(0.0016)	(0.0007)	(0.0013)	(0.0003)
Log likel.		−769.31		Observations		589
Chi-square		419.09***		McFadden pseudoR^2		0.214

*** p<0.01; ** p<0.05; * p<0.10.

Note: The marginal effects are the derivatives of the probabilities from the logit regression with respect to the regressors. Standard errors are in parenthesis.

The results for the two alternative specifications in agriculture are shown in Tables 3 and 4. The capital stock per worker is found to contribute to regional divergence in labor productivity as it increases the probability that below-average regions will move towards the bottom of the distribution. At the same time, capital per worker impedes the chances for poor regions to converge to higher productivity levels and for rich regions to move closer to the mean. Among the components of capital, the main driving forces behind divergence appear to be machinery and fertilizers. Fertilizers have a positive effect on all three states with initial above-average productivity, but the magnitude of the coefficient for those regions moving away from the mean and towards the top of the distribution is the largest. The role of irrigation is ambiguous because it prevents below-average regions from slipping further towards the bottom of the distribution, but at the same time increases the chances of above-average ones to strive towards even higher productivity levels.

Table 6: Marginal effects in the multinomial regression for services

	Below/ same	Below/ lower	Below/ higher	Above/ same	Above/ lower	Above/ higher
Capital	−0.0236***	−0.0194***	0.0082**	0.0152***	0.013***	0.0067***
	(0.0039)	(0.0044)	(0.0036)	(0.0029)	(0.0029)	(0.0018)
Mobile phones	0.0019***	0.0003	0.0014***	−0.002***	0.0000	−0.0014***
	(0.0003)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0004)
Loans	−0.007	−0.0121*	0.0218***	0.0072	−0.0049	−0.005
	(0.0047)	(0.007)	(0.005)	(0.005)	(0.0055)	(0.0039)
Government spending	0.0007*	0.0008	−0.0021***	0.0009**	−0.0008**	0.0004*
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0002)
Infrastructure	−0.0003	0.0011***	−0.0014***	0.0009***	−0.0006*	0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
FDI	0.046***	0.0415***	0.007	−0.041***	−0.0439***	−0.0093
	(0.0086)	(0.0128)	(0.009)	(0.0104)	(0.0117)	(0.0058)
Education	−0.0371*	−0.0388	0.0132	0.0169	0.0078	0.038**
	(0.0218)	(0.0294)	(0.0304)	(0.0259)	(0.0242)	(0.019)
R&D	−0.0447	0.0266	−0.1068**	0.1208***	−0.0228	0.0269
	(0.0318)	(0.0391)	(0.0431)	(0.0351)	(0.0361)	(0.0172)
Trade	−0.007***	−0.0096***	0.0036**	0.0071***	0.0049***	0.0012
	(0.0014)	(0.0025)	(0.0015)	(0.0014)	(0.0014)	(0.001)
Log likel.		−734.54		Observations		589
Chi-square		529.89***		McFadden pseudoR^2		0.265

*** p<0.01; ** p<0.05; * p<0.10.
Note: The marginal effects are the derivatives of the probabilities from the logit regression with respect to the regressors. Standard errors are in parenthesis.

Land has a similarly ambiguous effect. [13] In the specification with capital per worker, an additional hectare of sown land increases the probability that above-average regions converge towards mean productivity by 50%, but this coefficient is not robust once capital is replaced with its components. Both climate-related variables strengthen mean convergence for below-average regions, but for above-average regions temperature makes divergence from the mean more likely while precipitation has no significant effect. Electricity usage is the only variable that consistently and significantly contributes to convergence by increasing the probability of transitions towards the mean from both ends of the distribution. Environmental pollution affects only below-average regions and increases their likelihood of diverging away from the mean. Loans and government spending on agriculture also amplify regional polarization. R&D spending has a similar effect, but it is relevant only for

[13] Some marginal effects, especially for the land variable, exceed the value of 1. This is mainly because the marginal effects are computed at the sample means of the regressor variables. When the marginal effects are instead averaged across regions, the magnitude of the coefficients is less than 1.

above-average regions transitioning towards even higher productivity levels, while education promotes persistence in the initial state and does not seem to have a robust effect on intradistributional dynamics. Foreign trade helps below-average regions to converge towards the mean, whereas for above-average regions its effect is inclined towards divergence but not robust across specifications.

The estimated marginal effects for industry are presented in Table 5.[14] Capital per worker decreases the probability of divergence from the mean at both ends of the distribution but this effect is significant only for below-average regions. Taxes and FDI encourage persistence at higher levels of initial labor productivity but for below-average regions these factors significantly contribute to mean convergence. Interestingly, industrial pollution also boosts labor productivity for regions with lower output per worker levels, but this also needs to be seen in the context of the negative impact of pollution on agricultural productivity. In contrast, infrastructure and state ownership of industrial firms make it more likely that above-average regions will move towards the mean but at the same time these variables also drag productivity of below-average regions towards the bottom of the distribution. As in agriculture, education and R&D spending are relevant only for the above-average regions and promote persistence and even divergence from the mean. Foreign trade and loans to industrial firms are the only two factors that consistently contribute to mean convergence from both ends of the distribution.

The results for the service sector in Table 6 suggest that capital per worker, foreign trade, and telecommunications contribute to mean convergence from both ends of the distribution. Capital per worker also increases the probability for above-average regions to diverge but the magnitude of the coefficient is small relative to those responsible for convergence. Regional divergence is driven mainly by government spending, infrastructure, and FDI. Loans to service sector industries strengthen the chances for mean convergence but only for below-average regions. In contrast, education helps above-average regions to move towards the top of the distribution, while R&D spending preserves the status quo at the higher levels of productivity but also prevents regions with below-average productivity from moving up the distribution.

In summary, R&D spending, education, infrastructure, and government spending were found to amplify regional disparities in labor productivity across all sectors while trade, physical capital, and loans (except in agriculture)

[14] Due to the large amount of industrial capital per worker, the marginal effects of capital in this sector are expressed in thousand yuan per worker (in 1978 constant price) to avoid coefficients with a very small magnitude.

promote convergence across provinces. The estimation also indicates that other factors, such as FDI and industrial pollution, have opposite effects across different sectors. These results are not directly comparable to previous empirical studies due to differences in methodology as well as our focus on intradistributional dynamics and convergence as opposed to a basic identification of the determinants of labor productivity. But our conclusions are broadly in line with the existing literature. For instance, Henderson *et al.* (2007) show that physical capital accumulation narrowed the gap in output per worker across Chinese provinces, while technological change and human capital had the opposite effect. Similarly, Jefferson *et al.* (2008) illustrate that the industrial sector in central and northeastern China is more capital intensive relative to the coastal provinces where textile and apparel firms are clustered. This industrial composition helped interior provinces catch up with coastal regions because labor productivity is generally higher in capital-intensive industries, thus underlining the contribution of physical capital to regional convergence. Lastly, Ito (2010) and Chen and Song (2008) confirm that technology, R&D spending, and government spending exacerbate regional disparities in agricultural labor productivity.

CONCLUSIONS

China's transition over the past three decades has been marked by rapid economic growth and a major structural transformation, coupled with large and increasing regional disparities. This paper examines the growth of labor productivity in the three main sectors of the Chinese economy in the context of regional convergence by employing a novel methodology and new sectoral data over the period 1978–2006. The results show that all three sectors experienced major shifts in productivity across regions but with different patterns. In agriculture and services, the persistence at both ends of the productivity distribution was high, while those regions with output per worker levels at or around the mean exhibited strong tendencies to move away from it. This divergence pattern has led to a gradual shift from a unipolar to a bipolar distribution in the primary and tertiary sectors. By contrast, the secondary sector, despite its high extent of intradistributional mobility, has shown far less polarization across regions. One major reason is that regions with higher productivity have moved closer to the mean over time.

Our findings further indicate that regional disparities in sectoral productivity are mainly driven by R&D spending, human capital, and infrastructure, whereas convergence across provinces generally benefits from physical capital and international trade. From a policy perspective, the most relevant variables are those that help regions with initial below-average productivity move towards higher levels of output per worker. Besides physical capital and foreign trade, FDI has a positive effect in this regard but only in the secondary sector. Similarly, loans are beneficial to low-productivity provinces but only in the secondary and tertiary sectors. Interestingly, sector-specific government spending was found to be negatively associated with the chance of moving towards higher levels of productivity in agriculture and services, but corporate taxation in the industrial sector has a positive impact. Industrial pollution of the environment raises the prospects for below-average regions to catch up with their more productive counterparts in the secondary sector, but the resulting negative externalities prevent their agricultural sector to achieve the same goal.

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