Convergence in Labor Productivity across Provinces and Production Sectors in China

Qin, Weiguang and Bhattarai, Keshab

University of Hull, Business School, England, UK, Ludong University, Business School, YanTai, China

15 December 2021

Convergence in Labor Productivity across Provinces and Production Sectors in China

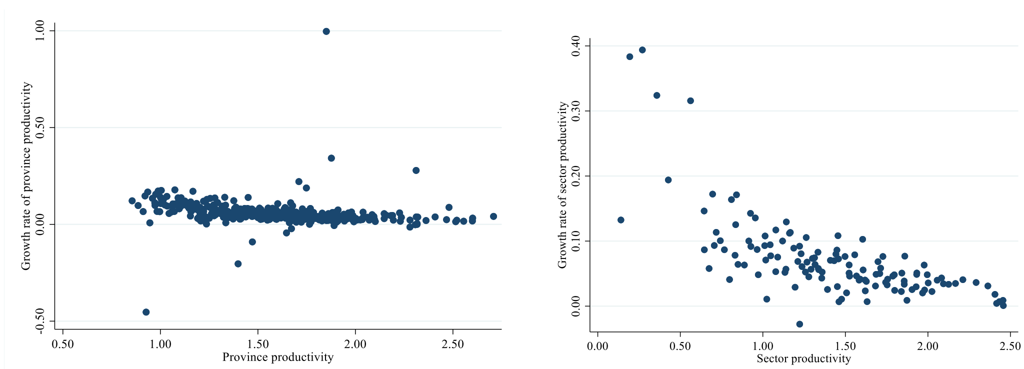
Abstract: The panel data analysis for labour productivity convergence across provinces and sectors in China shows existence of unconditional and conditional convergence among them. While the human capital is found to have positive and significant effects on growth rates of sector-wise productivities, the FDI had positive and significant effects on growth rates of productivity across provinces. According to quantile regression, the convergence are asymmetric among provinces and sectors. The policy implications of this analysis is that low productivity sectors should improve human capital and reduce concentration for growing faster. Similarly provinces with low productivity could encourage more FDI to complement domestic investment for achieving higher rates of growth in labour productivity. This study also finds that greater inequality lowers the rate of labour productivity and hence causes more divergence across provinces. Effects income inequality on productivity are asymmetric and heterogeneous by quantiles and hence demand for an egalitarian redistribution system.

Key Words: productivity convergence, quintile growth regression, China

JEL classification: O4, O5

1. Introduction

China's economy has achieved rapid growth in the past 40 years since the reforms and opening up the economy in 1978. China now is the biggest consumption market of iron, oil, and cement in the world though huge resource input is becoming unsustainable. With the economic growth slowing down and changes in the international economic environment, China has been implementing supply-side structural reforms from 2015, for economic transformation and sustainable growth. Among all of them, productivity of labour is the most important factor that affects the economic transformation of provinces and sectors in the Chinese economy. In this context we aim to assess whether the growth is based on productivity promotion and whether the provinces or sectors with lower productivity are growing faster to converge to those with higher productivity and income.



a b

Figure 1 Scatter of provincial productivity and growth rate

The theory of convergence is one of the most important issues in analysis of economic growth. Part (a) of figure 1 is scatter plot of level of productivity across provinces in x-axis and their growth rates in y-axis from year 2006 to 2019. This shows slightly negative relation between the level of productivity and growth rate of productivity. Picture (b) is a scatter plot of productivity by sectors and their growth rates from year 2003 to 2019. This also shows negative relation between the level of productivity and its growth rates. Thus, if higher level of productivity results in lower growth rate of productivity and lower level productivity implies higher growth rates of it; there must be a convergence across provinces or sectors on labour productivity over time with its implications on more equality in real wages across sectors and provinces.

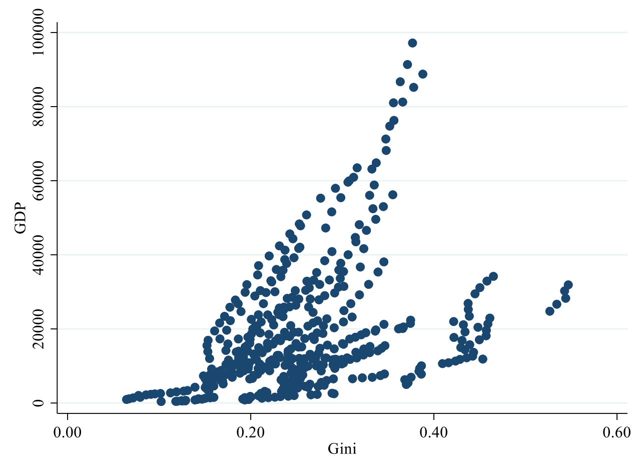


Figure 2 Scatter of provincial per capita GDP and Gini index

Along with miracles in economic growth, the income inequality across households, provinces has risen dramatically in China. Figure 2 shows that Gini index across provinces and level of per capita GDP have positive relation. Does such income inequality contribute to productivity convergence across provinces and sectors? Is there macroeconomic evidence that rising inequality harming on economic growth? How such inequality is affecting microeconomic channels on the ability of firms to harness the talents of potential innovators across the income spectrum?

This paper focus on productivity convergence or divergence among sectors or provinces, assessing the impacts of human, fix capital and FDI on productivity. The results and conclusions are contrasted with to the studies of other countries that that are engaged in transforming their economies. Conclusions of study will benefit policymakers who are responsible to set of policies on growth and equality.

2. Literature review on convergence in labour productivity

Most studies of labor productivity convergence are mainly focused on country wise or sector level analysis of western economies. Few studies focus on labor convergence of China, but are not comprehensive enough by provinces or sectors of production. This study looks into the convergence in labour productivity of China by provinces and sectors and factors that determine such convergence.

Country level convergence: In a recent study Hamrouni(2022) found out that the differences in knowledge accumulation rate and specialization (innovation or imitation) cause differences in productivity between northern and southern countries. Walheer(2021) revealed how the existence of heterogeneity in technology brings intra-regional convergence phenomena (mostly due to capital–labor ratio change), but no inter- regional convergences (owning to capital–labor ratio and technological changes). Demir and Duan(2018) explored the productivity convergence dynamics between the host and the productivity-frontier country, and found no significant effect of bilateral FDI flows on either host country productivity growth or on the productivity gap between the host and the frontier country.

Glocker and Wegmueller(2018) found how the decline in labor productivity growth is particularly striking for European countries and Japan and rather mild in Anglo-Saxon economies. Naveed and Ahmad(2016) considered the role of structural change in testing labor productivity convergence, and the results show that conditional convergence exists at country, regional and industry levels. Wang, et al.(2019) confirms a “catch-up” effect that provinces of China with lower TFP levels tend to grow faster than others, estimates show that higher growth rates of educational attainment, R&D, and intermediate goods density (per unit of labor) can enhance TFP growth.

Sector wise convergence: Domínguez, et al.(2021) found that the convergence of service-related industries and high-tech manufacturing industries have contrasting convergence-divergence patterns, robust convergence is only found for service-related industries. Kinfemichael and Morshed(2019) examined sectoral unconditional convergence in labor productivity in the US states, the results demonstrate a general slowing down in the rate of convergence of labor productivity. Lee(2009) research results indicated that long-run productivity convergence in manufacturing was trade-related as well as FDI-related. McErlean and Wu(2003) indicated that agricultural labor productivity diverges in China between 1985 and 1992, but converges between 1992 and 2000. Martino(2015) revealed a clear process of unconditional convergence for financial and business-related market services, but did not find such evidence for manufacturing and aggregate productivity. Kinfemichael and Morshed(2019) found unconditional convergence in real labor productivity for the service sector using disaggregated service sector data for 95 countries.

Convergence influencing factors: Mugera, et al.(2012) found factor intensity and efficiency changes are sources of labor productivity convergence while technical change is source of divergence. Lee and McKibbin(2018) found that faster productivity growth in the service sector in Asia contributes to sustained and balanced growth of Asian economies, but the dynamic adjustment is different across economies. Bijsterbosch and Kolasa(2010) presents empirical evidence of the effect of FDI inflows on productivity convergence in Central and Eastern Europe, results show that there is a strong convergence effect in productivity and FDI inflow plays an important role in accounting for productivity growth but critically depends on the absorptive capacity of recipient countries and industries. AlKathiri(2021) suggested that capital accumulation is the main driver of the observed unconditional convergence in productivity, whereas technological change is contributing to divergence rather than convergence in it.

3. Methodology and data

3.1 Methodology

Two popular methods for convergence analysis are β or σ-convergence. β -convergence implies that less developed districts performs better (catches up) on average when compared to more developed districts. In β-convergence regression framework based on the difference equation, the effect of labor productivity in t-1 period should be negative on change in labour productivity between t and t-1 periods. In contrast the idea behind σ-convergence is that the variance of (log) labor productivity among provinces or sectors decreases over time as production techniques spread among them making them similar in productivity terms.

Productivity may converge to a common steady state for all provinces or sectors, and also may convergence to different steady states for different subsets of provinces or sectors. To that end, the concept of β convergence is further divided into two types: unconditional and conditional convergence. The former analyzes whether all provinces or sectors converge to a common steady state, whereas the latter refers to different subsets converging to their respective steady states that are conditioned by province-specific or sector-specific characteristics. Here, the concept of β convergence builds on the notion that province or sector that is further away from its steady state level experiences faster productivity growth. This can be motivated by marginal productivity of capital, imitation, and positive catch-up and spill-over effects across provinces or sectors during the process of economic development.

3.1.1 Unconditional convergence

Unconditional convergence relates to converging to a common steady state. As a result an empirical test thus builds on a regression of productivity growth on initial productivity level. This convergence relation can be written in the following general functional form:

$$\Delta y_{i,t} = f(y_i^*, y_{i,0}) \tag{1}$$

Where $\Delta y_{i,t}$ the growth rate of labor productivity. y_i^* is the steady state level of labor productivity of the province or sector i, and $y_{i,0}$ is the initial level of labor productivity. We follow the specification by Mulder and De Groot(2007) to estimate the implied rate of productivity convergence, that is, $\beta = -(1 - e^{-\gamma\tau})$. The parameter γ, defined as $\gamma = -ln(\hat{\beta} + 1)/\tau$, is called the implied rate of convergence, and τ is the time interval. Higher is the value of γ, greater is the rate of convergence.

The linear relationship between $\Delta y_{i,t}$ and $y_{i,t-1}$ estimates the convergence for provinces or sectors. If the coefficient on $y_{i,t-1}$ is negative, then corresponding productivity is converging. If the relationship is positive then it is a sign of divergence. Therefore, the convergence equation for labor productivity per person in panel of observations can be written as follows:

$$\Delta y_{i,t} = \alpha + \beta y_{i,t-1} + u_{i,t} \tag{2}$$

3.1.2 Conditional convergence

As mentioned above, conditional convergence allows different subsets of provinces or sectors to converge to different levels, depending on province-specific or sector-specific conditions. One way of modeling conditional convergence is by controlling for individual specific fixed effects and time period fixed effects:

$$\Delta y_{i,t} = \alpha + \beta y_{i,t-1} + \mu_i + \eta_j + u_{i,t} \tag{3}$$

Where μ_i and η_t represent the spatial fixed effects and the time period specific effects, respectively.

All other variables are the same as in Eq.(2). A more informative and possibly more adequate model is the model which contains controls:

$$\Delta y_{i,t} = \alpha + \beta y_{i,t-1} + \theta x_{it} + \mu_i + \eta_j + u_{i,t} \tag{4}$$

Where x_{it} is a 1×K row vector of exogenous variables (in this case, in logs) and θ a K×1 column vector of coefficients.

3.1.3 Quantile regression

Eqs. (1) to (4) are estimated in the framework of the ordinary least squares regression (OLS), which only solves the sample mean. However, the quantile regression (QR) incorporates the estimates of different distributions of the dependent variables (Canarella and Pollard, 2004). Thus, the quantile regression can provide complementary evidence to encompass the convergence at extreme conditions. Additionally, the QR has better estimation performance than the OLS because it is less susceptible to outliers, skewness, and heterogeneity. Generally, quantile regression can be presented as follows:

$$Q_{y_i}(\tau|x) = C(\tau) + x_i'\beta(\tau) \tag{5}$$

In Eq. (5), y is the dependent variable, and x is a vector of independent variables. $Q_{y_i}(\tau|x)$ denotes the τ-th conditional quantile of y, and $0 < \tau < 1$. $\beta(\tau)$ and $C(\tau)$ denote the estimated coefficients and unobserved effect at quantile τ, respectively. We use the following equation to estimate the coefficient $\beta(\tau)$ of the τ-th quantile of the conditional distribution:

$$\beta(\tau) = argmin_{\beta \in R^P} \sum_{i=1}^{n} \rho_\tau(y_i - x_i'\beta(\tau) - C(\tau)) \tag{6}$$

In this equation, $\rho_\tau(u) = u(\tau - I(U < 0))$ is the check function, and $I(\cdot)$ is an indicator function $(u = y_i - x_i'\beta(\tau) - C(\tau))$.

We select seven quantiles, namely, low quantiles (0.1, 0.2), median quantile (0.4, 0.5, 0.6), and high quantiles (0.8, 0.9). The low and high quantiles consider the estimates at lower and upper tails of the conditional distribution of growth rate, respectively. Therefore, the low and high quantiles represent the downward and upward conditions, respectively. Median quantile represents the normal condition.

3.2 Data

In this study, we estimate the value of β-convergence and the speed of convergence. We use fixed effect estimation method for panel data for 31 provinces and 8 sectors of China. The data analyzed throughout this study are drawn from China National Bureau of Statistics; sample data of provinces ranges from 2006 to 2019 and sample of sectors is for 2003-2019. The labor productivity is defined by total real wage divided by total employment. It is assumed that the real wage grows in China with labor productivity.

Variables affecting labor productivity can be divided into internal and external factors. For sectors we take industrial concentration measured by Harphindal-Hirchman Index (HHI) and real human capital (HC) as representative of internal factors, foreign direct investment (FDI) represents an external factor.

As for provinces we choose fixed physical capital formation (FC) and human capital as internal factors and foreign direct investment as external factor. We take Gini index of income inequality by provinces to measure the impact of inequality on growth.

Industrial concentration: Modern technological innovation needs a large amount of investment in scientific research. Large enterprises usually have a high product market share and relatively stable operating income, so they can invest a lot of money into R&D to promote technological innovation. On the contrary, although number of small enterprises have incentives for innovation, they lack enough funds and research specialists. This paper uses the Herfindahl-Hirschman index (HHI) to represent the size of industrial concentration, which has a positive impact on technological progress and thus on economic growth. The data on HHI is derived from the Choice database.[a]

Foreign direct investment: FDI has positive spillover effects on domestic enterprises and scientific research institutions working for improving domestic innovation in China. FDI not only introduce foreign capital to alleviate the shortage of industrial funds, but also brings foreign advanced management experience and technical equipment into China. This promotes domestic technology required for the improvement of production efficiency. At the same time, FDI may also have a crowding-out effect on the innovation activities of domestic enterprises and institutions. The increase of FDI may restrain China's domestic independent innovation activities. Thus net effect of FDI on productivity can be positive or negative. The data on FDI are derived from the Ministry of Commerce of China. The data of human and physical capital are derived from Human Capital of China 2020.

Human and physical capital: Technological innovation is the outcome of the continuous process of human capital formation to create new knowledge aimed at stimulating productivity growth. The larger stock of human capital, the more new creation of technology and knowledge. Domestic investment creates more capital stock (RFC) which is an important element to raise the labor productivity, usually more capital stock is conducive to the increase of labor productivity.

Gini index: We adopt Gini index as the measure of income inequality as is common to literature in income inequality.es. For the lack of Gini index for provinces, we calculated this index according to Tian(2012) method. All the nominal data are deflated by GDP deflation index, in order to eliminate the inflation effects.

4. Results and discussions

4.1 β convergence analysis

We start the empirical section with β convergence analysis. β convergence focuses on the

---

[a] For the lack of industrial HHI index, we averaged HHI index of mining, manufacturing, electricity, heat, gas and water production and supply.

relationship between the initial level of a variable (i.e., productivity) and its growth rate. A significant, negative β indicates that provinces or sectors with low productivity catch up with provinces or sectors with high productivity. By including the key determinants of productivity into the relationship, β convergence analysis provides insight not only into the differences in productivity among provinces and sectors but also into the driving forces behind convergence patterns. Thus, it provides information for policy-making. As a preliminary to the empirical analysis, we present the descriptive statistics (means, standard deviations (SD), min and max values across sectors and provinces in Table 1.

Table 1 Descriptive statistics of province variables

Group	Variable	Obs	Mean	Std.dev.	Min	Max
Province	Prod	434	1.563	0.382	0.762	2.708
	Gini	434	-1.411	0.352	-2.742	-0.604
	FDI	434	17.730	1.532	13.246	21.288
	HC	434	8.969	1.053	5.817	11.530
	FC	434	7.237	1.341	3.689	10.377
Sector	Prod	136	1.367	0.524	0.124	2.457
	FDI	136	15.151	1.508	12.685	18.039
	HC	136	8.942	1.075	6.816	11.385
	HHI	136	6.313	0.896	4.399	9.210

Note: prod = labour productivity, output/employment; log of real FDI is thousand dollars; HC and FC measured in Billion yuans, HHI = Harphindal-Hirchman Index of industrial concentration.

And also we adopted three different methods for stationary testing of model variables of provinces and sectors as Table 2 shown. According to the results, in general variables are stationary but we also find that some of these variables are non-stationary and there are some differences between LLC, LM and IPS tests. However we find cointegration among model variable as the results shown in Table 3. Pedroni and Kao tests suggest significant Phillips-Perron and ADF statistics and Westerlund test shows significant variance ratio implying cointegration. In summary, most of the model variables are stationary but even if they are non-stationary (as prod, Gini and FDI),they are cointegrated. Thus we can proceed to panel regression analysis.

Table 2 Stationary test for provinces and sectors variables

Group	Variables	Levin-Lin-Chu		Hadri LM test		Im–Pesaran–Shin	
		Statistic value	P value	Statistic value	P value	Statistic value	P value
Province	Growth	-7.4577	0.0000	-0.3689	0.6439	-10.0349	0.0000
	Prod	6.6615	1.0000	40.7256	0.0000	-2.6137	0.0045
	Gini	5.0738	1.0000	41.0308	0.0000	-3.8860	0.0001
	FDI	5.5318	1.0000	34.2694	0.0000	-2.7929	0.0026

	HC	-9.0352	0.0000	42.1084	0.0000	-2.6162	0.0044
	FC	-11.7231	0.0000	41.9666	0.0000	3.9117	1.0000
Sector	Growth	-2.6462	0.0041	17.1523	0.0000	-5.3150	0.0000
	Prod	-6.2821	0.0000	27.1625	0.0000	0.3962	0.6540
	FDI	-3.5130	0.0002	21.4568	0.0000	-0.8823	0.1888
	HC	-1.1626	0.1225	26.5019	0.0000	1.6997	0.9554
	HHI	17.5142	1.0000	9.9969	0.0000	2.7399	0.9969

Table 3 Cointegration test for provinces and sectors variables

Test methods	Province		Sector	
	Statistic value	P value	Statistic value	P value
Phillips–Perron t	-14.8281	0.000	-11.4337	0.00
Augmented Dickey–Fuller t	-12.3493	0.000	-7.6917	0.00
Westerlund Variance ratio	-2.2783	0.0114	-2.0317	0.0211

In this section, we empirically analyze β convergence and σ convergence of cross-province and cross-sector productivity. First, we regressed each equation and applied Modified Wald test for heteroscedasticity, and pesaran cross section independence test to determine the overall significance of the model. As Table 4 shows the data have heteroscedasticity and cross correlation properties. In addition, by Hausman tests random effect panel data models were rejected in favour of fixed effects models. Thus, White and Newey -West estimation is adopted for fixed effects model of province and sector analysis, to eliminate heteroscedasticity and cross correlations, the results are shown in Table 5 and table 7.

Table 4 Test of heteroscedasticity and cross correlation of province regression

Group	Models	Modified Wald test for Heteroscedasticity		Pearson test for cross sectional independence	
		Statistical value	Prob	Statistical value	Prob
Province	Unconditional model	10865.24	0. 00	19.611,	0. 00
	Conditional model	5996.78	0. 00	8.724	0. 00
	Conditional model with controls	3670.32	0. 00	7.539	0. 00
Sector	Unconditional model	12432.59	0. 00	7.115	0. 00
	Conditional model	1627.07	0. 00	7.232	0. 00
	Conditional model with controls	146.45	0. 00	4.026	0. 00

First, we analyze convergence across provinces. If convergence exist the β coefficient should be negative. As the estimation results are presented in Table 5, the second column presents the unconditional convergence results, the coefficient β of province model is negative and statistically significant at 1% level, indicating the existence of β convergence. The implied rate of convergence of province is 0.0964. The third column in Table 5 shows the estimated conditional convergence model. The hypothesis that the time-period fixed effects are jointly insignificant was rejected at the 1% significance level, justify controlling for time period fixed effects. The β coefficient of province is -0.652, significant and negative, indicating conditional convergence. The column 4 and column 5 estimated convergence with controlling variables and dynamics. Column 5 FDI is 0.0263 and significant at 5% level, indicating that FDI significantly increase the productivity in a province. The coefficient of $Growth_{t-1}$ is -0.0804 and significant at 1% level, indicating that the lagged growth rate of productivity has negative influence on next period. A comparison of these columns shows that the β coefficient substantially decreased from -0.0919 to -0.79 and the implied rate increased from 0.096 to 1.5606. Furthermore, the adjusted R^2 increased from 0.1686 (column 2) to 0.5254 (column 4), indicating that the controlling explanatory variables contributed to convergence.

Table 5 β convergence models of province productivity robust estimation

Variables	Unconditional model	Conditional model	Conditional model with controls	Conditional model dynamic with controls
$Prod_{t-1}$ (β)	-0.0919***	-0.652***	-0.666***	-0.790***
	(0.0198)	(0.180)	(0.184)	(0.0341)
Implied rate: τ	0.0964	1.0556	1.0966	1.5606
Year		0.0460***	0.0423***	0.0603***
		(0.0145)	(0.0110)	(0.00388)
FDI			-0.00842	0.0263**
			(0.0101)	(0.0113)
HC			0.0810	-0.00963
			(0.0613)	(0.0406)
FC			-0.00546	-0.0418
			(0.0399)	(0.0271)
Province				-0.00369
				(0.00259)
$Growth_{t-1}$				-0.0804***
				(0.0306)
Constant	0.198***	-91.55***	-84.60***	-120.1***
	(0.0338)	(28.93)	(22.16)	(7.677)
R^2	0.1686	0.5205	0.5254	
Observations	403	403	403	372
Number of groups	31	31	31	31

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Compared to the OLS estimation, the QR considers the estimates of normal and extreme observations of the dependent variable, thereby providing more comprehensive evidence. Results for the quantile regression conditional of convergence of productivity by provinces provide results that expand on the one obtained through linear regression in Table 3.

Considering analysis that income inequality and productivity effects simultaneously, we include the Gini index in the equation. In Table 6 are results fit for quantile regression models at different quantile levels are presented. The output yields valuable information about β-convergence coefficients as we can observe different outcomes at each quantile level. The parameter of β is significant and negative, so that there exists convergence among provinces at all quantiles. Further the coefficient of β at 0.8 and 0.9 quantiles are higher than others, so that the convergence speed is lower. That means the productivity convergence are asymmetric at different quantiles of provinces.

The coefficients of year, however, are more diversely, at 0.1, 0.5 and 0.6 quantiles are positive and insignificant at 1% level; at 0.8 quantile are negative and significant. That means the influences of year are changing corresponding to different quantile of productivity growth rate by provinces. There is a tendency for poor provinces to converge faster as expected. In the case of FDI, the effects are significant and positive except 0.1, 0.5 and 0.9 quantiles, indicating that FDI would stimulate productivity in most provinces, but in some circumstance like lower or higher quantile wouldn't. Which evidenced the role of absorptive capacity in determining the impact of FDI on productivity growth and is consistent with the findings of Bijsterbosch and Kolasa(2010) research. The magnitude of human capital on labour productivity growth rate tends to be significant and negative at most quantiles, indicating that human capital could improve productivity convergence in most circumstances. As for fix capital, the coefficient is positive and significant at 0.1 and 0.6 quantiles, negative and significant at 0.5 and 0.8 quantiles. That means the effect of fix capital are diverse across provinces corresponding to different labour productivity growth rate.

Table 6 Quantile regression of province productivity and income inequality convergence in China

Variables	0.1	0.2	0.4	0.5	0.6	0.8	0.9
$Prod_{t-1}$ (β)	-0.219***	-0.170**	-0.168***	-0.262***	-0.152***	-0.0637***	-0.0666
	(0.0709)	(0.0740)	(0.0475)	(0.0480)	(0.0126)	(3.42×10^{-06})	(0.00)
$Gini_{t-1}$	-0.0193***	-0.0832	-0.0123	-0.0426*	-0.0282***	0.00889***	0.0163
	(0.00611)	(0.0694)	(0.0210)	(0.0241)	(0.00816)	(1.35×10^{-05})	(0.00)
Year	0.0130**	0.0112	0.00895*	0.0181***	0.00701***	-0.000154***	-0.000893
	(0.00661)	(0.00902)	(0.00497)	(0.00505)	(0.00103)	(7.20×10^{-07})	(0.00)
FDI	0.00348	0.00867**	0.00668***	0.00155	0.00913***	0.000619***	-0.00129
	(0.00470)	(0.00370)	(0.00238)	(0.00158)	(0.00129)	(2.66×10^{-06})	(0.00)
HC	-0.0257***	-0.0277*	-0.0332**	0.0299***	-0.0268***	-0.00420***	-3.96×10^{-05}
	(0.00743)	(0.0148)	(0.0148)	(0.0106)	(0.00248)	(2.08e-06)	(0.00)
FC	0.00465***	0.00544	0.00432	-0.0337***	0.00703***	-0.00127***	-0.00130
	(0.000991)	(0.00399)	(0.00455)	(0.00773)	(0.00180)	(2.48×10^{-06})	(0.00)
Observations	403	403	403	403	403	403	403
Number of groups	31	31	31	31	31	31	31

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Now let us turn to sectors. Productivity gains in sector X may affect sector Y productivity, thus we expect to see some correlations across industries as many production linkages exist between different sectors. The estimation results of sector convergence are presented in table 7. The unconditional convergence of coefficient β is negative and statistically significant at 1% level, indicating the existence of β convergence among sectors. The implied rate of convergence of sector is 0.101 as for provinces. The conditional convergence model of third column shows that the time-period fixed effects are jointly insignificant was rejected at the 1% significance level, justify controlling for time period fixed effects. The β coefficient of sector is -0.282, significant and negative, indicating conditional convergence. The coefficient of HC in Column 4 and column 5 are 0.082 and 0.0368 respectively and significant at 1% level, indicating that human capital significantly increase the productivity in a sector. The coefficient of $\text{Growth}_{t\text{-}}1$ is 0.285 and significant at 1% level, indicating that the lagged growth rate of productivity has positive influence on next period. A comparison of these columns shows that the β coefficient substantially decreased from -0.0961 to -0.226 and the implied rate increased from 0.101 to 0.2562. Furthermore, the adjusted R^2 increased from 0.458 (column 2) to 0.638 (column 4), indicating that the controlling explanatory variables contributed to convergence.

table 7 β convergence models of sector productivity robust estimation

Variables	Unconditional model	Conditional model	Conditional model with controls	Conditional model dynamic with controls
Prod_{t-1} (β)	-0.0961***	-0.282***	-0.216***	-0.226***
	(0.0110)	(0.0481)	(0.0563)	(0.0393)
Implied rate: τ	0.1010	0.3313	0.2433	0.2562
Year		0.0151***	0.00409	0.00880***
		(0.00365)	(0.00566)	(0.00303)
FDI			-0.00545	0.000480
			(0.00332)	(0.00695)
HC			0.0820***	0.0368***
			(0.0184)	(0.00988)
HHI			-0.00739	-0.00370
			(0.00601)	(0.00446)
Sector				0.0198***
				(0.00680)
Growth_{t-1}				0.285***
				(0.0662)
Constant	0.200***	-29.99***	-8.479	-17.75***
	(0.0164)	(7.274)	(11.21)	(6.077)
R^2	0.4584	0.5112	0.6385	
Observations	128	128	128	120
Number of groups	8	8	8	8

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Observing Table 8, we can note that the coefficients of β are significant and negative across sectors in all quantiles, indicating sector convergence is satisfied. The coefficients of year are insignificant at 0.1 and 0.2 quantile, meaning that no fix year effect at low tail. However, year effect of other quantile is negative and significant (except 0.6 quantile is positive), indicating that productivity tends to convergence over time at middle and upper tail. In the case of FDI, the coefficients are significant and negative except 0.1 and 0.6 quantiles, indicating that FDI contribute to sector productivity convergence in most circumstances. This also means that FDI have no effect if productivity growth rate is very low.

The magnitude of human capital on labour productivity growth rate are significant and positive at all quantile, indicating human capital benefit for sector productivity improvement. Furthermore, it is easy to find that the positive coefficients are smaller at high quantiles. These results indicate that the impact of human capital on sector productivity growth rate is heterogeneous. As for HHI, the coefficient is negative and significant except 0.2 quantile. That means higher industrial concentration benefit for labour productivity convergence across sectors.

Table 8 Quantile regression of sector productivity convergence in China

Variables	0.1	0.2	0.4	0.5	0.6	0.8	0.9
$Prod_{t-1}$ (β)	-0.0509***	-0.0488***	-0.0471***	-0.0502***	-0.0765***	-0.0426***	-0.0410***
	(0.00302)	(0.00168)	(0.00275)	(0.00236)	(0.00398)	(0.000821)	(0.000569)
Year	-0.000524	-0.000898	-0.00251**	-0.00143***	0.00149***	-0.00214***	-0.00217***
	(0.000565)	(0.00222)	(0.00108)	(0.000549)	(0.000526)	(0.000198)	(0.000293)
FDI	-0.00181	-0.00138**	-0.00282**	-0.00140**	-0.000796	-0.00166***	-0.00180***
	(0.00124)	(0.000638)	(0.00118)	(0.000655)	(0.000964)	(0.000320)	(0.000291)
HC	0.00604***	0.00543***	0.00581***	0.00627***	0.00630***	0.00266***	0.00318***
	(0.000683)	(0.00122)	(0.000730)	(0.000487)	(0.000645)	(0.000397)	(0.000296)
HHI	-0.00454***	-0.00311***	-0.00211	-0.00448***	-0.0106***	-0.00218**	-0.00410***
	(0.00158)	(0.00116)	(0.00225)	(0.00164)	(0.00136)	(0.00108)	(0.000327)
Observations	128	128	128	128	128	128	128
Number of groups	8	8	8	8	8	8	8

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

4.2 Robust analysis

For the robust test, we adopted σ convergence by means of the development of the standard deviation of productivity in levels. The result is presented in Figure 3, which shows an overall downward trend in the dispersion of province productivity over the period 2006–2019. The annual standard deviation of province productivity decreased from 0.2476 in 2003 to 0.2059 in 2014. In 2014-2015, however, there was an increase, immediately followed by a downward movement during the period 2015-2019. As western China development policy encourages industrial transfer from eastern coastal provinces to Midwestern provinces to optimize the spatial layout of productivity, the productivity among provinces converge. The σ convergence of sectors result is presented in Figure 4, there is an increasing trend from year 2003 to 2008, then overall decreasing trend up to 2019. As China government adopted Eliminate backward production capacity and encourage “internet +” policies, different industries adopted new technologies, thus improved convergence in sectoral productivity. To conclude, Figure 3 and Figure 4 supports σ convergence.

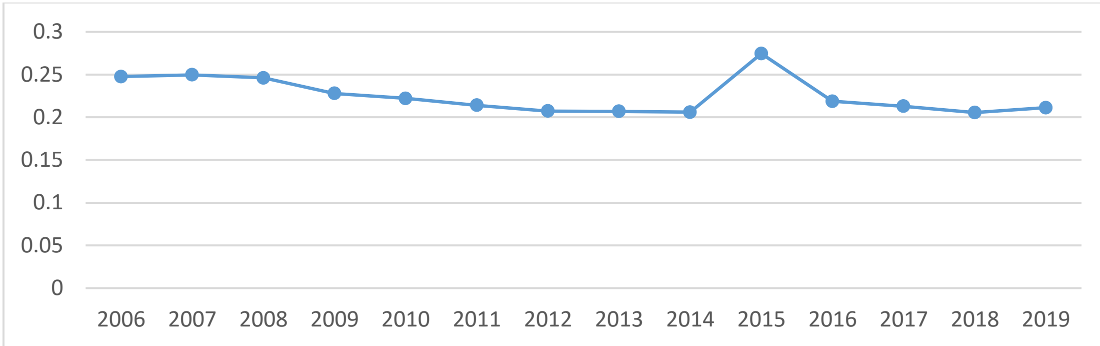


Figure 3 σ-convergence across provinces

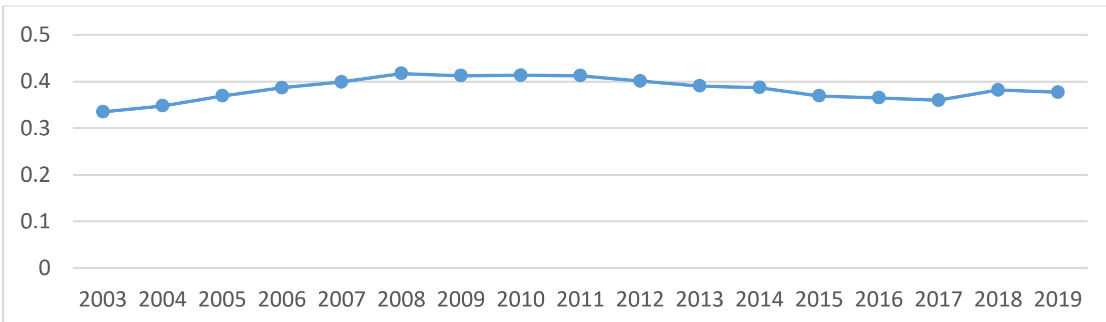


Figure 4 σ-convergence of across production sectors

4.3 Equality and convergence

We extend the empirical analysis of convergence in investigating whether more equality contributes or not to convergence in labour productivity. We adopted Gini index, well known measure for the income inequality for this purpose. General hypothesis is that more income inequality causes more divergence if the coefficient of Gini index is positive. That is a positive coefficient on Gini index implies more inequality contributes towards divergence.

Table 9 Test of heteroscedasticity and cross correlation of province inequality regression

Models	Modified Wald test for heteroscedasticity		Pearson test for cross sectional independence	
	Statistical value	Prob	Statistical value	Prob
Unconditional model	28475.97	0.00	14.274	0.00
Conditional model	24989.34	0.00	14.089	0.00
Conditional model with controls	28081.22	0.00	11.493	0.00

Consistent with the analysis above, we regressed each equation and applied Modified Wald test for heteroscedasticity, and pesaran to test for cross section correlations to determine the overall significance of above empirical model. As Table 9 shows that the data suffers from heteroscedasticity and cross correlation properties. Thus, White and Newey estimation is adopted for province panel data analysis, the results are shown in Table 10. In addition, Hausman tests of a random effects model versus a fixed effects model was rejected.

As Table 10 shows, the coefficient on Gini index of unconditional convergence in second column is -0.137 and statistically significant at 1% level, indicating inequality contribute to convergence. That means if a province has more inequality then it will result in e low productivity differences. Column 3 to column 5 estimated conditional convergence with controlling variables and dynamic terms, the coefficient of $Gini_{t-1}$ from -0.0912 to -0.311 and significant at 1% level, conformed that inequality could reduce productivity increase and thus lead to convergence.

Table 10 inequality and productivity convergence robust estimation

Variables	Unconditional model	Conditional model	Conditional model with controls	Conditional model dynamic with controls
$Gini_{t-1}$ (β)	-0.137***	-0.0912***	-0.0934***	-0.311***
	(0.0309)	(0.0208)	(0.0288)	(0.0890)
year		-0.00174	0.00302	-0.00892**
		(0.00107)	(0.00277)	(0.00355)
FDI			0.0121	0.0582***
			(0.00880)	(0.0182)
HC			-0.0430	-0.00672
			(0.0260)	(0.0634)
FC			-0.0186	0.0566
			(0.0231)	(0.0398)
province				0.0207***
				(0.00351)
$Growth_{t-1}$				-0.471***
				(0.0379)
Constant	-0.138***	3.431	-5.847	15.87**
	(0.0419)	(2.155)	(5.427)	(7.174)
R^2	0.0723	0.0737	0.0792	
Observations	403	403	403	372
Number of groups	31	31	31	31

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Referring quantile analysis of income inequality effect are obtained in table 4. As in Table 6, we can note that in most cases the coefficients of $Gini_{t-1}$ are negative, and significant at 0.1 and 0.6 quantiles, indicating at lower and middle quantiles saw more income inequality resulting in slower productivity growth. However, at 0.8 quantiles is positive and significant, that means in certain cases income and productivity growth could increase simultaneously. Note also that the coefficient is positive but insignificant at 0.9 quantile, meaning that income inequality have no effect on productivity growth at upper tail. To the conclusion of above analysis, the effect of income inequality on productivity is asymmetric and heterogeneous.

5. Conclusions and policy recommendations

We have analyzed σ convergence, unconditional and conditional β convergence of cross-province and cross-sector labour productivity empirically based on a panel data set of 31 Chinese provinces and 8 sectors over the period 2003–2019.

We analyzed the determinants of trends in convergence. Evidence on β convergence revealed unconditional convergence among provinces and sectors owning to large scale disparity in their economic structures. As a further verification of such nature of conditional convergence in labor productivity either two-way fixed effects model or a richer model controlling for other determinants and lags were estimated. While the first fixed effect model revealed significant conditional convergence, the second model with FDI, human capital and income inequality revealed even stronger conditional convergence as the bias of the estimator of β was reduced further adding explanatory power of these augmented models.

FDI has played an important role in increasing province productivity. Hence, in the coming Five-Year Plan, more FDI inflow into China should be encouraged through more regionally and sectorally targeted economic policies. Apparently, its role in technological advancement will help bridging the technological gap and will greatly improve the cross-province convergence if FDI directed to provinces with low labour productivity.

Human capital is essential to enhance productivity across sectors. Human capital input in some sectors are more than in others. This results in uneven distribution in productivity. Thus, the sectors that lack enough of human capital should pay more attention on accumulation of skills of its human resources of professional and technical personnel.

Income inequality is found to have significant and negative impacts on economic growth. Thus, government of China should pay more attention to equality by ensuring that more people benefit from economic growth, more equality will promote economic growth further.

References:

AlKathiri, N. "Labour productivity growth and convergence in manufacturing: A nonparametric production frontier approach." *Applied Economics* (2021): 1-24.

Bijsterbosch, M., and M. Kolasa. "FDI and productivity convergence in Central and Eastern Europe: an industry-level investigation." *Review of World Economics* 145, no. 4(2010): 689-712.

Canarella, G., and S. Pollard. "Parameter heterogeneity in the neoclassical growth model: a quantile regression approach." *Journal of Economic Development* 29(2004): 1-32.

Demir, F., and Y. Duan. "Bilateral FDI Flows, Productivity Growth, and Convergence: The North vs. The South." *World Development* 101(2018): 235-249.

Domínguez, A., F. Santos-Marquez, and C. Mendez. "Sectoral productivity convergence, input-output structure and network communities in Japan." *Structural Change and Economic Dynamics* (2021).

Glocker, C., and P. Wegmueller. "International evidence of time-variation in trend labor productivity growth." *Economics Letters* 167(2018): 115-119.

Hamrouni, D. "International diffusion of knowledge labor productivity and catching up between North and South." *International Review of Economics & Finance* 77(2022): 170-178.

Kinfemichael, B., and A. K. M. M. Morshed. "Convergence of labor productivity across the US states." *Economic Modelling* 76(2019): 270-280.

Kinfemichael, B., and A. K. M. M. Morshed. "Unconditional convergence of labor productivity in the service sector." *Journal of Macroeconomics* 59(2019): 217-229.

Lee, J. "Trade, FDI, and productivity convergence: A dynamic panel data approach in 25 countries." *Japan and the World Economy* 21, no. 3(2009): 226-238.

Lee, J., and W. J. McKibbin. "Service sector productivity and economic growth in Asia." *Economic Modelling* 74(2018): 247-263.

Martino, R. "Convergence and growth. Labour productivity dynamics in the European Union." *Journal of Macroeconomics* 46(2015): 186-200.

McErlean, S., and Z. Wu. "Regional agricultural labour productivity convergence in China." *Food Policy* 28, no. 3(2003): 237-252.

Mugera, A. W., M. R. Langemeier, and A. M. Featherstone. "Labor productivity convergence in the Kansas farm sector: a three-stage procedure using data envelopment analysis and semiparametric regression analysis." *Journal of Productivity Analysis* 38, no. 1(2012): 63-79.

Mulder, P., and H. L. F. De Groot. "Sectoral Energy- and Labour-Productivity Convergence." *Environmental and Resource Economics* 36, no. 1(2007): 85-112.

Naveed, A., and N. Ahmad. "Labour productivity convergence and structural changes: simultaneous analysis at country, regional and industry levels." *Journal of Economic Structures* 5, no. 1(2016).

Tian, W. "Gini coefficient calculation and its change trend analysis in China." *The Journal of Humanities*, no. 02(2012): 56-61.

Walheer, B. "Labor productivity and technology heterogeneity." *Journal of Macroeconomics* 68(2021): 103290.

Wang, S. L., et al. "Are China's regional agricultural productivities converging: How and why?" *Food Policy* 86(2019): 101727.

Zhang, Junsen. 2021. "A Survey on Income Inequality in China." *Journal of Economic Literature*, 59 (4): 1191-1239