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Convergence in labor productivity across provinces and production sectors in China

Keshab Bhattarai [a,*], Weiguang Qin [b]

[a] University of Hull, Business School, England, UK
[b] Ludong University, Business School, YanTai, China

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ABSTRACT

Empirical evidence is found for the β and σ convergence towards the steady states of labor productivity across provinces and production sectors in China based on estimates of static, dynamic and quintile panel data models. The pattern of convergences is found to be asymmetric across sectors according to quantile panel regression estimations. The pattern of convergence was more obvious when controls for human capital, FDI, industrial concentration and inequality were introduced for the robustness of our analysis. While the effects of human capital and FDI on productivity convergence are asymmetric across provinces and sectors, more inequality or higher rate of industrial concentration lead to divergence either in simple or quantile panel estimations. Implications these findings are clear. Policies that promote competition and more equal distribution are better for convergence in labour productivity across provinces and sectors in China.

1. Introduction

China's economy has achieved rapid growth in the past 40 years with gradual reforms and opening up since 1978. China now is the biggest consumer of iron, oil, and cement in the world though huge resource input like this is increasingly becoming unsustainable. Concerned with slow-down in economic growth and changes in the international economic environments, China started implementing supply-side reforms for structural transformation and sustainable growth in 2015. Market reforms aim to make China a single market, therefore prices of goods and factors should converge as a result of mobility of resources across provinces and sectors according to the marginal productivities. Convergence in labour productivity across provinces and sectors has received attention of policy makers. In this context we aim to assess whether the provinces or sectors with lower productivity are growing faster to catch up the income levels of those currently with higher labour productivity and income. Do we observe beta convergence in labour productivity across thirty-one provinces and eight production sectors in China? Are they moving towards the same steady state? Do patterns of convergence vary by human capital (HC), FDI, or inequality (Gini index) in provinces or industrial concentration (HHI) among sectors? Is the convergence symmetric or asymmetric across quintiles of productivity distribution? How do sigma convergence measures compare to beta convergence measures? Does more inequality lead to greater divergence from the steady state? We seek answers to these questions from our analysis.

The issue of growth convergence is one of the most important elements in the theory of economic growth. Part (a) of Fig. 1 is a

* Corresponding author.
E-mail address: k.r.bhattarai@hull.ac.uk (K. Bhattarai).

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scatter plot of level of productivity, measured by the real wage rate[1], across provinces of China on x-axis and their growth rates on y-axis from year 2006–2019. This shows slightly negative relation between the level of productivity and growth rate of productivity. Picture (b) is a scatter plot of labor productivity by sectors and their growth rates from year 2003–2019. This shows clear negative relation between the level of productivity and its growth rates. Thus, if higher level of productivity relate to lower growth rate of productivity and lower level productivity implies higher growth rates of it in this manner, there must be a convergence across provinces or sectors on labour productivity over time, implying more equality in real wages across sectors and provinces over a reasonable model horizon.

Along with miracles in economic growth, the income inequality across households, provinces have risen dramatically in China. Fig. 2 shows positive relations between the Gini indices across provinces and level of per capita GDP. Does such income inequality contribute to productivity convergence across provinces and sectors? Does rising inequality harm on economic growth? Does high degree of inequality open up microeconomic channels whereby firms tend to harness talents of profit motivated potential innovators across the income spectrum?

We provide a brief review of the relevant literature in section 2. It follows specification of the unconditional, conditional and quantile growth convergence models as well as statistical properties of data on model variables including physical and human capital, industrial concentration, and Gini index used to assess the productivity convergence or divergence among sectors or provinces in section 3. The results and conclusions from this study are presented in section 4 and contrasted to findings in some other studies relevant to us. Conclusions of study and policy implications are drawn in the last section.

2. Literature review on convergence in labour productivity

Most studies of labor productivity convergence focus on country wise or sector level analysis of western economies. Few studies that exist on labor convergence of China are not comprehensive enough by provinces or sectors of production. Our study aims to fill that gap by looking into the convergence in labour productivity more comprehensively across all thirty-one provinces and eight sectors of production in China; we will quantify the impacts of key factors that determine such convergence.

Country level convergence: A brief review of literature is important to motivate our model as well as to compare our findings to existing studies relevant to our research context. In a recent theoretical review Hamrouni (2022) found out that differences in knowledge accumulation rate and specialization (innovation or imitation) cause differences in productivity between northern and southern countries. This partly motivates use to keep human capita as a control variable. Walheer (2021) by applying non-parametric decomposition analysis revealed how the existence of heterogeneity in changes in technology brings intra-regional convergence phenomena but not inter-regional convergences mostly due to changes in capital–labor ratios; we also have sectoral and provincial focus. Demir and Duan (2018) assessed the impact of FDI productivity convergence dynamics between the host and the productivity-frontier country by panel regressions, 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. FDI is another control in our estimations. While Glocker and Wegmueller (2018) adopted time-varying parameters median-unbiased estimation and found how the decline in labor productivity growth was particularly striking for European countries and Japan and rather mild in Anglo-Saxon economies; we look into similar issue in China, which is now the second largest economy in the world. Naveed and Ahmad (2016) found empirical evidence for existence of conditional convergence at country, regional and industry levels considering the role of structural changes in testing labor productivity convergence by GMM panel regressions. We also have panel models for quintiles of productivity distributions.

Sector wise convergence: A production sector represents groups of similar firms. As the production technology varies by one sector to another, so does the labour productivity. Domínguez et al. (2021) using parametric and nonparametric frameworks contrasts the patterns of convergence or divergence in productivity of service-related industries and high-tech manufacturing industries; robust convergence is only found for service-related industries. Kinfemichael and Morshed (2019a, 2019b) examined sectoral unconditional convergence in labor productivity in the US states. Their results demonstrate a general slowing down in the rate of convergence of labor productivity among US states. Wang et al. (2019) confirms "catch-up" effects so that provinces of China with lower TFP levels tend to grow faster than those with higher TFP levels in agriculture sector. Kinfemichael and Morshed (2019a, 2019b) found unconditional convergence in real labor productivity for the service sector using disaggregated service sector data for 95 countries. Lee (2009) using dynamic panel data model found that long-run productivity convergence in manufacturing was related to trade and FDI in 25 countries. Mcerlean and Wu (2003) indicated how the agricultural labor productivity diverged in China between 1985 and 1992, but converged 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. None of the existing studies have taken convergence in labour productivity across sectors for China. This motivates us for it.

Control variables for convergence analysis: As stated earlier the neoclassical growth model underlies our analysis. Labour productivity mainly depends on intensity of capital input, and tends to converge to the steady state. In addition to high saving rate in China there are a number of complementary factors that determine shape or size of labor productivity function. Mugera et al. (2012) using DEA, parametric and semiparametric regressions found factor intensity and efficiency to be sources of labor productivity

[1] We appreciate an anonymous referee for confirming our measure of labour productivity by stating that if the production function for each province/sector is Cobb-Douglas so that the profit maximization condition is $w_{it} = \theta p_{it} y_{it} / n_{it}$ where w is the wage, p is the price of the good, θ is the labor share, y is output, and n is effective labor input then the real wage, w/p can be used as a measure of labour productivity. The movement of the real wage is one for one with movement in output per worker (see Parente and Prescott, 2002; MIT Press).

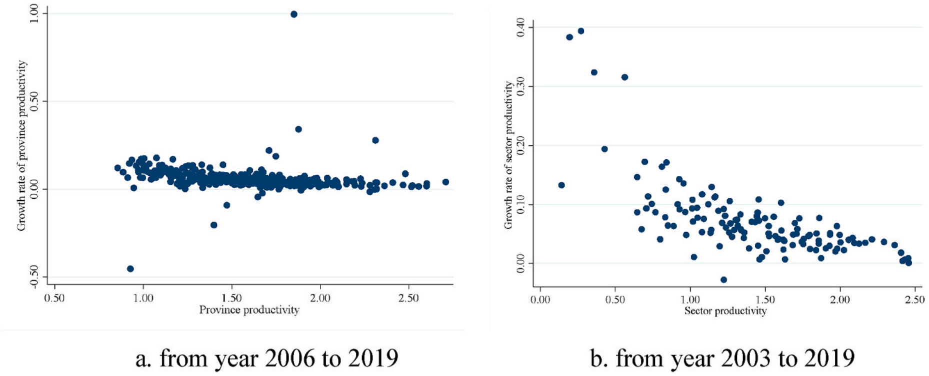

Fig. 1. Scatter plot of provincial or sectoral labor productivity and productivity growth rates.

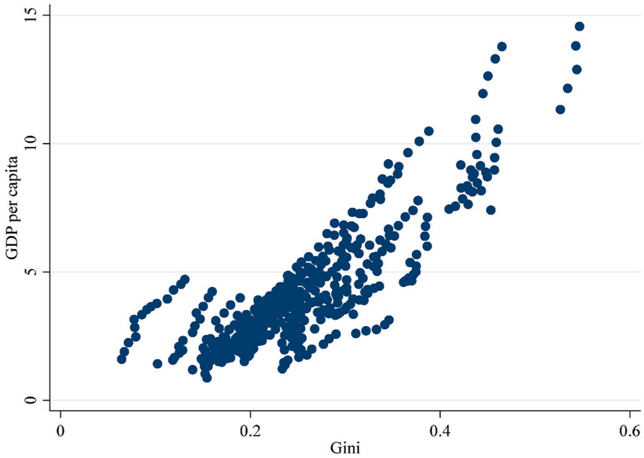

Fig. 2. Scatter plot of Gini index and per capita GDP across provinces, 2006 to 2019.

convergence while technical changes causing for divergence. Lee and Mckibbin (2018) using an empirical general equilibrium model found that faster productivity growth in the service sector in Asia contributes to sustained and balanced growth of Asian economies, but the process of dynamic adjustment is different across economies. Bijsterbosch and Kolasa (2010) present empirical evidence of the effect of FDI inflows on productivity convergence in Central and Eastern Europe based on OLS, GMM and SUR regressions. Their results show that there is a strong tendency for convergence in productivity growth due to FDI inflow but that critically depends on the absorptive capacity in recipient countries and industries. Alkathiri (2021) suggested that capital accumulation is the main driver of the observed unconditional convergence in productivity in manufacturing, whereas technological change is contributing to divergence rather than convergence among them. Wang et al. (2019) estimates show how higher growth rates of educational attainment, R&D, and intermediate goods density (per unit of labor) can enhance TFP growth.

Thus, a brief review of convergence literature as cited above use DEA, OLS, GMM, semiparametric regression and panel data analysis for empirical research. Some studies also contain sector wise convergence for within sector convergence analysis for China. We contribute to this literature by adopting a more comprehensive approach with static and dynamic simple and quantile panel regressions for assessing provincial and sectoral convergences or symmetric or asymmetric patterns of convergence across them.

3. Methodology and data

3.1. Methodology

The β and σ convergence are the two popular measure for convergence analysis in the growth literature. The concept of β-convergence is linked to the neoclassical growth model, which predicts that the growth rate of a region is positively related to the distance that separates it from its steady-state. Thus, depending on the differences in marginal productivity of capital for provinces or sectors at different stage of development, β-convergence implies that less developed districts (sectors) performs better (catches up) on average to more developed districts (sectors). The concept of σ-convergence focuses on how the level of cross-sectional dispersion, measured as the sample variance, changes over time. Note that there can be situations where β and σ convergence concepts are not necessarily linked. Indeed, β-convergence is a necessary but not a sufficient condition for σ-convergence. Therefore, absence of σ-convergence can co-exist with β-convergence.

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 convergences. 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 panel data model for convergence

Unconditional convergence relates to converging to a common steady state. 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:

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

where $\Delta y_{i,t}$ is 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. The steady state level of productivity for a region also depends upon other different variables that control for the regional differences (Durlauf et al., 2005; Durlauf & Quah, 1999).

Consider $lny_{i,t} = \alpha + (1-\beta)lny_{i,t-1} + u_{i,t}$; 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:

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

We follow the specification by (Barro and Sala-i-Martin, 2004 or Mulder & De Groot, 2007) to estimate the implied rate of productivity convergence, that is, $\beta = -(1 - e^{-\gamma\tau})$. The parameter γ, defined as $\widehat{\gamma} = -\frac{ln(\widehat{\beta}+1)}{\tau}$ is called the implied rate of convergence, and τ is the time interval and we choose one year for simplicity. It is customary to have an intercept term in a linear regression, therefore we retain α, it makes estimations easier and also picks up common factors underlying change sin the productivity.

3.1.2. Conditional panel data model for convergence

As mentioned above, conditional convergence allows different subsets of provinces or sectors to converge to different levels of steady state, 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:

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

where μ_i and η_t represent the spatial (sectoral) fixed effects and the time period specific effects, respectively. All other variables are the same as in Eq.**Error! Reference source not found.**. A more informative and possibly more adequate model is the model, abundantly found in growth literature, contains other controls:

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

where $x_{i,t}$ is a $1 \times K$ row vector of exogenous variables (in this case, in logs) and θ is a $K \times 1$ column vector of coefficients on determining factors.

3.1.3. Panel quantile regression

Equations (1)–(4) set modelling framework for simple and dynamic panel data models estimated either by least squares regression (OLS) or the GMM estimators, intended to find the best fit of the sample mean relations. However, relations may differ by the quantile location of it, it is desirable to pick up asymmetric relations across quantiles if they exist. The panel quantile regression (QR) fulfills that gap by making estimators specific to quantile locations of dependent variables (Canarella and Pollard (2004)). Thus, quantile regressions can provide complementary evidence to encompass the convergence at extreme conditions and other specific range of the productivity distribution. Additionally, the panel QR model has better estimation performance than the simple static or dynamic panel OLS or GMM models because it is less susceptible to outliers, skewness, and heterogeneity. Generally, a specific quantile regression can be presented as follows:

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

In Eq. (5), y is the dependent variable, and x is a vector of independent variables. $Q_{yi}(\tau|x)$ 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:

$$\beta(\tau) = argm\, in_{\beta \in R^p} \sum_{i=1}^{n} \rho_\tau\left(y_i - x_i'\beta(\tau) - C(\tau)\right) \tag{6}$$

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 productivity growth rate, respectively. Median quantile represents relations for the central location of the distribution.

3.2. Data

In this study, we estimate the value of β-convergence and the speed of convergence in real wages, using panel data of thirty-one provinces and eight sectors of China[2]. We derive the labour productivity measure by dividing the total real wage bill by total employment both for provinces and sectors.

We eliminate business cycle effects in variables by applying HP Filter to the data using a smoothing parameter equal to 100 following referee suggestions. This allows analysis not to be distorted by the cyclical elements in the data. We assume the production follows Cobb-Douglas function of constant returns to scale, that means the real wage grows in accordance with labour productivity.[3] Our QR model is relevant to adjust for the surge in productivity development process across provinces and sectors. China have implemented western development project since year of 2000, which facilitate inter-provincial investment and mobility of technology and personnel effectively ultimately resulting in changes in the level of productivity.

All of data are mainly drawn from China National Bureau of Statistics; sample of provinces ranges from 2006 to 2019 and sectors is for 2003–2019. For lack of provincial employment data, we take total employed persons in urban units as proxy for provincial employment (its unit is ten thousand persons). Similar to provincial employment, the total wages of employed persons in urban units is taken for wage variable (its unit is hundred million yuan). Sectoral data of employment is measured by the number of employees (unit is ten thousand persons); the sectoral wage measured by total wages of employees (the unit is hundred million yuan). GDP deflator is to convert nominal wage bill to real wage bill.

Other control variables affecting labor productivity can be divided into internal and external factors. For sectors we take industrial concentration measured by Herfindahl-Hirschman Index (HHI) and real human capital (HC) as representative of internal factors, foreign direct investment (FDI) to represent for external factors. 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 another external control for provinces.

Industrial concentration: Any 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 innovations. On the contrary, most 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. Such concentration has a positive impact on technological progress and thus on economic growth (Parente & Prescott, 2002). The data of HHI is derived from the Choice database.[4]

Foreign direct investment: FDI not only alleviates the shortage of industrial funds for firms, but also brings foreign advanced management experiences and technical equipment into China. These will improve domestic innovation and technology which contribute to efficiency in production. Since reforms and opening up of 1978, FDI has continuously flowed in eastern provinces in the early stage followed by a fast growth rate and the higher level of productivity. Gradually FDI inflows started spreading towards the middle and western provinces. These provinces then experienced faster growth and better level of technology. Thus, FDI should contribute to productivity convergence across provinces and sectors. The data on FDI are derived from the Ministry of Commerce of China.

Human and physical capital: Chinese central government invests massively in infrastructure construction across different provinces and contributes to accumulation of provincial physical capital stock. Investment in education and health also creates provincial human capital and so does migration. Workers can move between provinces easily, for example lots of farmers from western provinces go to eastern province for a work, thus the accumulation of physical and human capital benefits economic growth. Thus, steady states across provinces of China is not only affected by saving rate and technology, but also affected by the stock of physical and human capital. The data of human and physical capital are derived from the Human Capital of China 2020.

Gini index: Alesina and Perotti (1996) argued that high income inequality, "by increasing the probability of coups, revolutions, mass violence or, more generally, by increasing policy uncertainty and threatening property rights, has a negative effect on investment and, as a consequence, reduces growth". How the level of inequality affects economic growth have been studied from different aspects (Ahluwalia, 1976; Alesina & Rodrik, 1994; Barro, 2000; De La Croix & Doepke, 2003; Galor & Tsiddon, 1997, pp. 363–382). Following this literature, we develop a hypothesis that the Gini index as the measure of income inequality has a discernible impact on divergence on economic growth across provinces and sectors. For the lack of Gini index for provinces, we construct this index according to

[2] Eight sectors are: agriculture, forestry, animal husbandry and fishery sector, industry sector, construction sector, transportation sector, warehousing and postal service sector, wholesale and retail sector, accommodation and catering industry sector, financial sector, real estate sector.

[3] Real wage is nominal wage deflated by CPI.

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

statistical method from China Statistics (Tian, 2012). All the nominal data are deflated by the GDP deflator in order to eliminate inflation effects and to base analysis in terms of real variables.

4. Discussion of estimated results in convergence analysis

4.1. *β convergence analysis of labour productivity*

We start the empirical section with β convergence analysis. β convergence focuses on the relationship between the initial level of a variable (i.e., productivity) and its growth rate. A significant, negative β coefficient 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 across provinces and sectors. Thus, it provides information for policy-making. As a preliminary to the empirical analysis, we first present descriptive statistics of model variables (means, standard deviations (SD), min and max values across sectors and provinces in Table 1.

We adopted three different methods for stationary tests for province and sector variables as shown in Table 2. According to the results, we could conclude that productivity, FDI HHI and Gini variables are non-stationary, although there are some differences between tests. Therefore, we test cointegration of model variables, the results are shown in Table 3, and enough conclude that model variables are cointegrated and have long run relations as suggested by Phillips-Perron, ADF and Westerlund tests. Thus, we conclude that variables that are not stationary are cointegrated and thus we can proceed for regression.

4.2. *Test for stationarity and cointegration*

In this section, we first empirically analyze β convergence and σ convergence across provinces and sectors. Then we will assess the impact of income inequality on productivity. Using fixed effect and dynamic panel data model we estimate each equation of the model. Then we apply Modified Wald test to determine existence of heteroscedasticity, and used Pesaran's cross section independence test to determine the correlation across provinces or sectors to ascertain 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 models were rejected in favor of fixed effects models; we apply robust estimations to correct for hetroscedasticity and cross-sectional correlations. Thus, White and Newey -West estimation is adopted for fixed effect models of provincial, sectoral and inequality analysis, which could eliminate heteroscedasticity and cross correlation, the results are shown in Table 5, Tables 9 and 12.

4.3. *Robust estimation of convergence across provinces in simple panel models*

First, we analyze convergence across provinces. If convergence exist, the β coefficient should be negative. As the estimation results presented in Table 5 show, the β coefficients are negative and significant at 1% level of significant regardless of whether it is unconditional, conditional or dynamic panel regression models, indicating the productivity convergence happening across provinces. These results are robust. We also computed implied rate of convergence ($\hat{\gamma}$) following these β similar to Jiang et al. (2018) using the time interval of one year. The implied rate of convergence of provinces varies from 0.093 to 0.814. The column 4 and column 5 estimated convergence with more control variables and using dynamic panel mode of Arellano and Bond GMM estimator. Coefficient on FDI in column 5 is 0.00705 and significant at 1% level, indicating that FDI could improve provincial productivity significantly but may cause divergence. The coefficient of HC is negative and significant which means human capital contributes to convergence in general. The coefficient of $Growth_{t-1}$ is 0.311 and significant at 1% level, indicating that there is persistent in growth rates; provinces and sectors that grew fast in the past continue to do so to some extent even in next years. The year fixed effects are significant and positive at the 1% level of significance. The province fixed effects are significant and negative at the 1% significance level. Both outcomes justify controlling for year and province fixed effects; more detailed estimations on them are given in Table 8.

Compared to the panel OLS estimations, the QR estimates provide relations by quantiles reducing the impacts of extreme

Table 1
Descriptive statistics of province variables.

Group	Variable	Obs	Mean	Std.dev.	Min	Max
Province	Prod	434	1.560	0.403	0.362	2.691
	Gini	434	0.259	0.087	0.064	0.547
	FDI	434	17.745	1.533	12.812	21.208
	HC	434	8.968	1.055	5.742	11.519
	FC	434	7.220	1.368	3.159	10.269
Sector	Prod	136	1.344	0.585	−0.884	2.479
	FDI	136	15.213	1.531	8.724	18.015
	HC	136	8.936	1.091	6.315	11.397
	HHI	136	6.313	0.896	4.399	9.210

Note: prod = labour productivity, output/employment; log of real FDI is thousand dollars; HC is human capital, FC is fix capital, HC and FC measured in Billion yuan, HHI = Herfindahl-Hirschman Index of industrial concentration. Gini is the measure of inequality.

Table 2
Stationary test for provinces and sectors variables.

Group	Variables	Levin-Lin-Chu		Hadri LM test		Im–Pesaran–Shin	
		Statistics	P value	Statistics	P value	Statistics	P value
Province	Growth	−10.245	0.000	8.464	0.000	−8.581	0.000
	Prod	6.662	1.000	40.726	0.000	−2.614	0.005
	Gini	5.074	1.000	41.031	0.000	−3.886	0.000
	FDI	5.532	1.000	34.269	0.000	−5.323	0.000
	HC	−55.591	0.000	41.765	0.000	−0.165	0.434
	FC	−100.000	0.000	39.586	0.000	−5.491	0.000
Sector	Growth	−7.514	0.000	3.873	0.000	−6.531	0.000
	Prod	−12.828	0.000	23.358	0.000	−3.737	0.000
	FDI	−3.513	0.000	21.457	0.000	−4.921	0.000
	HC	−8.981	0.000	26.303	0.000	−2.635	0.004
	HHI	17.514	1.000	9.997	0.000	2.740	0.997

Table 3
Cointegration test for provinces and sectors variables.

Test methods	Province		Sector	
	Statistics	P value	Statistics	P value
Phillips–Perron t	−14.093	0.000	−3.2704	0.0005
Augmented Dickey–Fuller t	−1.601	0.055	−2.3952	0.0083
Westerlund Variance ratio	−2.663	0.004	−1.2342	0.1086

Table 4
Test of heteroscedasticity and panel cross section dependence across provinces and sectors.

Group	Models	Modified Wald test for Heteroscedasticity		Pearson test for cross sectional independence	
		Statistical value	Prob	Statistical value	Prob
Province	Unconditional model	695.27	0.00	44.436	0.00
	Conditional model	1208.34	0.00	24.345	0.00
	Conditional model with controls	1688.17	0.00	20.591	0.00
Sector	Unconditional model	486.29	0.00	4.884	0.00
	Conditional model	1056.21	0.00	3.695	0.00
	Conditional model with controls	1974.41	0.00	5.316	0.00
Gini inequality	Unconditional model	2269.61	0.00	47.995	0.00
	Conditional model	1216.16	0.00	46.028	0.00
	Conditional model with controls	19414.83	0.00	18.438	0.00

observations on mean estimations and providing more precise estimations across quantiles. Results for the quantile regression of provincial productivity convergence thus extend the linear regression analysis shown in Table 5.

4.4. Convergence across provinces in quantile panel models

As shown in Table 6 the parameter β is significant and negative at each quantile level, so that there exists convergence among provinces at all quantiles. The coefficients of year fixed effects are significantly negative at 0.1, 0.4, 0.5 and 0.9 quantiles; over time different quintile had different and asymmetric growth experiences. The province fixed effects are significant at 0.1, 0.4, 0.5, 0.9 quantiles; thus province-wise convergence effects are also different across quantiles. For instance, coastal states with high income may be closing toward saturation to the steady state than the inner and western provinces. In the case of FDI, the effects are significant and negative at 0.1, and 0.8 quantiles, however significant and positive at 0.2, 0.4, 0.5 and 0.9 quantiles, indicating FDI effects are asymmetric across quintiles. Similar to FDI, the coefficients of HC are also asymmetric. FC are significant and negative except 0.2 quantiles, indicating fix physical capital could improve productivity convergence in most circumstances consistent to the neoclassical theory of declining marginal productivity of capital.

We also control for initial income while finding the effect of human capital, Gini, FDI and per capita GDP on productivity per unit of efficient labour units. As Table 7 shows the y_0 is the initial state of productivity, its coefficient is negative and significant, that means if the level of initial income is high in a province it will experience a lower productivity. This contributes to convergence. Gini is positive and significant at 10% level, that means inequality contributes to divergence. Table 8 shows heterogeneity fix effects by province on productivity. A province with high per capita GDP has slightly lower growth of productivity as it is closer to the steady state.

Table 5
βconvergence models of province productivity robust estimation.

Variables	Unconditional model	Conditional model	Conditional model with controls	Conditional model dynamic with controls
$Prod_{t-1}$ (β)	−0.179***	−0.548***	−0.557***	−0.0890***
	(0.0382)	(0.0726)	(0.0808)	(0.00443)
Implied rate: τ	0.197	0.794	0.814	0.093
FDI			0.00264	0.00705***
			(0.00226)	(0.000914)
HC			−0.0666***	−0.0287***
			(0.0189)	(0.00226)
FC			0.0361**	−0.0138***
			(0.0135)	(0.00161)
Year fixed effects		0.0327***	0.0335***	0.00582***
		(0.00602)	(0.00530)	(0.000247)
Province fixed effects		−4.063***	−4.138***	0.00146***
		(0.750)	(0.664)	(0.000167)
$Growth_{t-1}$				0.311***
				(0.00390)
Constant	0.342***	0.00	0.00	−11.33***
	(0.0615)	(0.00)	(0.00)	(0.486)
Observations	403	403	403	372
Number of groups	31	31	31	31

Standard errors in parentheses***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The unconditional, conditional, conditional model with controls are egressed with Driscoll-Kraay standard errors; the conditional dynamic panel model with controls are estimated by system GMM estimators in STATA.

Table 6
Quantile regression of province productivity convergence in China.

Variables	0.1	0.2	0.4	0.5	0.6	0.8	0.9
$Prod_{t-1}$ (β)	−0.0482***	−0.0641***	−0.0741***	−0.0390**	−0.0740***	−0.0395***	−0.0430***
	(0.000252)	(0.0194)	(0.00310)	(0.0192)	(0.0188)	(0.00485)	(0.00103)
FDI	0.00120***	−0.0109***	−0.00716***	−0.00545***	−0.00687	0.0264***	−0.00349***
	(8.32e-05)	(0.00360)	(0.00179)	(0.00133)	(0.00512)	(0.00652)	(0.000837)
HC	−0.000901***	0.00140	0.0198***	0.00874***	0.0186**	−0.0102***	0.00824***
	(9.14e-05)	(0.0138)	(0.00676)	(0.00241)	(0.00834)	(0.00221)	(0.00165)
FC	−0.00223***	−0.00526	−0.00784***	−0.00696**	−0.00896**	−0.0612***	−0.00669***
	(6.38e-05)	(0.00835)	(0.00130)	(0.00292)	(0.00348)	(0.0162)	(0.00119)
Year fixed effects	−0.00391***	−0.00120	−0.00198***	−0.00389**	−0.00193	0.00116	−0.00389***
	(2.30e-06)	(0.00128)	(0.000176)	(0.00160)	(0.00156)	(0.00131)	(0.000127)
Province fixed effects	0.000121***	0.000471***	0.000637***	−0.000246	1.32e-05	0.00675***	5.54e-05
	(6.87e-06)	(0.000129)	(0.000231)	(0.000626)	(9.79e-05)	(0.00183)	(3.94e-05)
Observations	403	403	403	403	403	403	403
Number of groups	31	31	31	31	31	31	31

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

Table 7
βconvergence models of province productivity per human capital (robust estimation).

Variables	Coefficient	std.err.	T	P>|t|
y_0	−0.0003	0.0001	−3.5200	0.0050
$Prod\_HC_{t-1}$	−0.0877	0.1758	−0.5000	0.6280
Gini	32.7722	15.3264	2.1400	0.0560
FDI	0.00001	0.00001	2.1400	0.0560
GDP	−0.0002	0.0001	−1.2100	0.2520
Constant	0.503777	1.67822	0.3	0.77

4.5. Convergence across sectors in simple panel models

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 interlinkages exist between different sectors. The estimation results of convergence by sectors are presented in Table 9. The unconditional convergence of coefficient β is negative and statistically significant at 1% level, indicating the existence of β convergence among sectors; the corresponding implied rate of convergence of sector is 0.529 percent. The β coefficient of conditional model is −0.576, significant and negative, indicating conditional convergence of 0.858 percent. The coefficient of FDI, HC and FC in Column 4 and column 5 are insignificant at 5% level, indicating that FDI, human capital and physical capital have no effect on sectoral productivity convergence. The coefficient of $Growth_{t-1}$ is −0.0465 and significant at 1% level, indicating that the lagged

Table 8
Province fix effects on productivity per efficient labour.

Variables	Coefficient	std.err.	t	P>|t|	Variables	Coefficient	std.err.	t	P>|t|
anhui	0	(empty)			Jilin	−4.8760	2.3632	−2.0600	0.0640
beijing	8.8476	7.5354	1.1700	0.2650	Liaoning	−2.3172	3.3908	−0.6800	0.5090
chongqing	−3.2009	2.3577	−1.3600	0.2020	Neimenggu	−3.4157	2.6701	−1.2800	0.2270
fujian	−1.9113	1.7244	−1.1100	0.2910	ningxia	0.7726	1.7451	0.4400	0.6670
gansu	−2.9723	3.7123	−0.8000	0.4400	qinghai	2.4140	4.2317	0.5700	0.5800
guangdong	0.0000	(omitted)			shaanxi	−0.9113	1.5537	−0.5900	0.5690
guangxi	−1.5306	1.0261	−1.4900	0.1640	shandong	7.8425	3.3046	2.3700	0.0370
guizhou	−2.3201	1.6361	−1.4200	0.1840	shanghai	−6.9592	6.4784	−1.0700	0.3060
hainan	−4.8713	3.2894	−1.4800	0.1670	shanxi	−0.7881	2.5172	−0.3100	0.7600
hebei	1.0296	0.7756	1.3300	0.2110	sichuan	3.4172	1.1217	3.0500	0.0110
heilongjiang	2.1930	1.2900	0.2230	−1.9970	tianjin	−9.4126	5.5438	−1.7000	0.1180
henan	6.3947	2.8415	2.2500	0.0460	xinjiang	−2.2556	1.4777	−1.5300	0.1550
hubei	1.0688	0.5682	1.8800	0.0870	xizang	1.3682	2.2593	0.6100	0.5570
hunan	1.8085	0.2784	6.5000	0.0000	yunnan	0.3562	0.8268	0.4300	0.6750
jiangsu	2.4169	1.5199	1.5900	0.1400	zhejiang	3.9393	1.2764	3.0900	0.0100
jiangxi	−1.5210	0.9698	−1.5700	0.1450					

Table 9
Robust estimation ofβconvergence models of sectoral productivity.

Variables	Unconditional model	Conditional model	Conditional model with controls	Conditional model dynamic with controls
$Prod_{t-1}$ (β)	−0.411***	−0.576***	−0.577**	−0.874***
	(0.0886)	(0.146)	(0.197)	(0.0760)
Implied rate: τ	0.529	0.858	0.860	2.071
FDI			−0.00432	−0.0202
			(0.0395)	(0.0184)
HC			−0.194*	0.0241
			(0.110)	(0.0294)
HHI			−0.0723	0.0167
			(0.0769)	(0.0105)
Year fixed effects		0.0178	0.0408***	0.0440***
		(0.0220)	(0.0125)	(0.00560)
Sector fixed effects		−7.760	−17.53***	0.183***
		(9.783)	(5.862)	(0.0243)
$Growth_{t-1}$				−0.0465***
				(0.0145)
Constant	0.689***	0.00	0.00	−88.10***
	(0.144)	(0.00)	(0.00)	(11.26)
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.

growth rate of productivity diminishes after a high growth episode. A comparison of these columns shows that the β coefficient substantially decreased from −0.411 to −0.874 and the implied rate of convergence increased from 0.529 to 2.071 percent, indicating that controlling for other explanatory variables contributes towards convergence.

Observing Table 10, we can note that the coefficients of β are significant and negative except at 0.1 and 0.2 quantiles, indicating that the higher the level of productivity the more likely is convergence in labour productivity. In the case of FDI, the coefficients are significant and negative at 0.8 and 0.9 quantiles, indicating that if sectoral productivity is higher, the FDI will improve convergence. The coefficient of HC is only significant and negative at 0.5 and 0.9 quantiles, and among the HHI coefficient only that at 0.5 quantile is significant, which means HC and HHI have no significant effect on sectoral convergence in most circumstance. These asymmetric results of quantile regression reveal the reason why coefficients on FDI, HC and HHI were insignificant in Table 9. The coefficients of year fixed effects are significant and negative at 0.8 and 0.9 quantiles, meaning that productivity tends to convergence over time at upper tail of the productivity distribution. Note that the sector fixed effects are positive and significant at 0.6 and 0.9 quantiles, reflecting that sector specific factors had no contribution on convergence in other quintiles.

4.6. A short analysis of σ convergence

We now examine σ convergence across provinces and sectors. These are measured by the standard deviation of productivity level across provinces and sectors over time. The results presented in Fig. 3 shows an overall downward trend in the dispersion of province productivity over the 2006–2019 period. The annual standard deviation of productivity across provinces decreased from 0.123 in 2007 to 0.0.005 in 2019. This must be due to western China development policy that encouraged spread of industrialization from Eastern coastal provinces to Midwestern provinces. This optimized the spatial productivity and led to sigma convergence among provinces. We

Table 10
Quantile regression of sectoral productivity convergence in China.

Variables	0.1	0.2	0.4	0.5	0.6	0.8	0.9
$Prod_{t-1}$ (β)	0.309	25,130	−0.110***	−0.0756***	−0.0850***	−0.0849***	−0.0743***
	(0.620)	(130,705)	(0.0269)	(0.0170)	(0.0209)	(0.00514)	(0.00211)
FDI	0.0460	50,549	0.0130	0.00431	0.0214	−0.00310***	−0.00237***
	(0.0720)	(263,618)	(0.0302)	(0.00347)	(0.0220)	(0.000750)	(0.000450)
HC	−0.135	24,508	−0.00187	−0.00811***	−0.0215	0.000909	−0.00740***
	(0.183)	(127,718)	(0.00573)	(0.00250)	(0.0273)	(0.00263)	(0.00176)
HHI	−0.187	19,457	−0.00522	−0.0447***	0.00865	−0.00496	−0.00241
	(0.223)	(101,590)	(0.0256)	(0.0123)	(0.0276)	(0.00363)	(0.00460)
Year fixed effects	0.0972	−21,228	−0.00328	0.00466**	−0.00440	−0.00395***	−0.00573***
	(0.155)	(110,863)	(0.00248)	(0.00233)	(0.00618)	(0.000772)	(0.000188)
Sector fixed effects	−0.0628	22,328	0.000299	−0.00709	0.0231**	0.00150	0.00365***
	(0.106)	(116,450)	(0.0153)	(0.00448)	(0.0114)	(0.00180)	(0.000979)
Observations	127	127	127	127	127	127	127
Number of groups	8	8	8	8	8	8	8

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

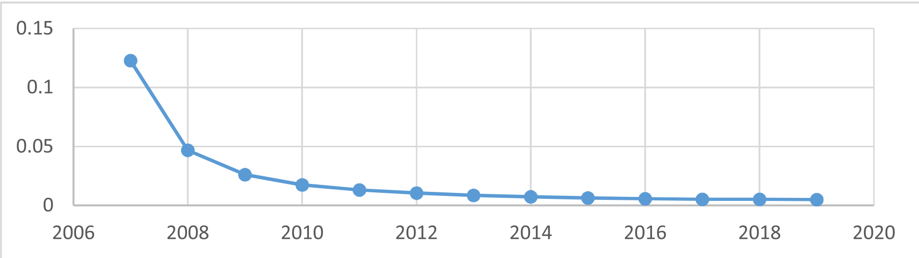

Fig. 3. Trend of implied σ-convergence across provinces in the estimations with HP filter.

similarly find that σ convergence in labour productivity of sectors declined from year 2003–2019 as presented in Fig. 4. We had removed the cycles in data using HP filter. This is the major reason for such patterns. Policy reasons behind such sectoral convergence in China may be government policy aiming to eliminate backwardness in production capacity and encourage sophisticated technology including the use of "internet +" policies. Many companies of different sectors adopted new technologies, thus improved convergence in sectoral productivity. Both Figs. 3 and 4 support σ convergence hypothesis for China.

4.7. *Inequality and convergence*

We extend the empirical analysis of convergence by investigating whether more inequality contributes or not to convergence in labour productivity across provinces. Similar to Zhang (2021) we find that income inequality rapidly increased in the first three decades since 1978 but stabilized and even slightly declined in the past decade, consistent with the well-known Kuznets hypothesis as China have achieved rapid economic growth.

Does more income inequality contribute to convergence in labour productivity? For this, observe the heterogeneity in inequality of labour productivity across provinces in Fig. 5. We had observed in earlier sections that in general coefficient of Gini index is positive across all static or dynamic panel data model estimations. Thus, there is a strong evidence that inequality causes more divergence in income across provinces in China. In fact we find a bi-directional Granger causality between inequality and productivity across provinces in China as shown in Table 11.

While there is a clear evidence of a positive relation between income inequality and per capita income, impacts of inequality in

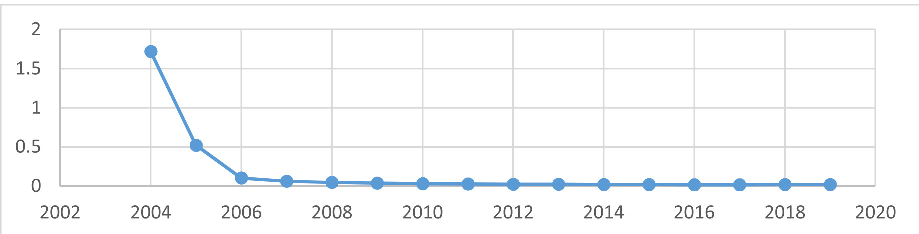

Fig. 4. Trend of implied σ convergence across sectors in the estimations with HP filter.

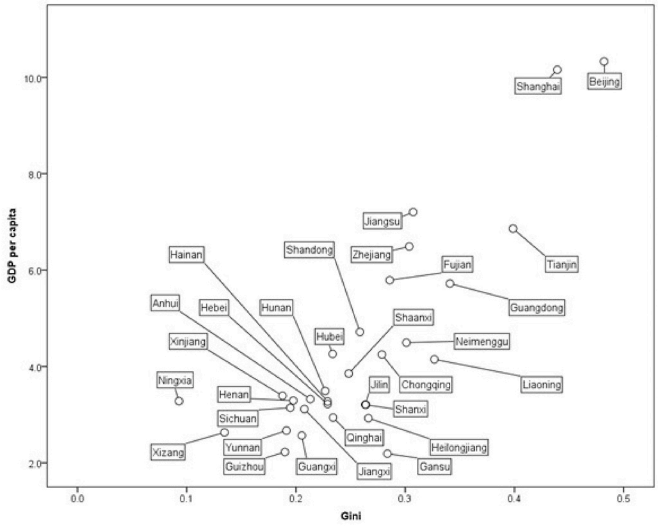

Fig. 5. Gini Index and GDP per capita across provinces in China.

Table 11
Granger non-causality test of provincial Gini and productivity.

H_0	Z-bar	Z-bar tilde
Gini does not Granger-cause productivity	77.8527***	50.2102***
productivity does not Granger-cause Gini	17.7512***	10.9521***

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

labour productivity are quite mixed as shown in Table 12. The coefficient on Gini index of unconditional convergence in second column is −0.348 and significant at 1% level, indicating inequality to contribute towards convergence but that effect disappears in the conditional model with controls. It contributes to conditional convergence in the dynamic model in the last column. Otherwise coefficients in other control variables FDI, HC, FC, year fixed effects, province fixed effects and $Growth_{t-1}$ are similar to those in Table 5.

As shown in Table 13, the coefficients of Gini are negative and significant at quantiles 0.4 and 0.9 but positive and significant and positive at 0.5 and 0.6 quantiles but insignificant at 0.1 and 0.2 quantiles. Thus, effects of inequality on labour productivity are mixed and asymmetric.

Now we are able to answer research questions posed in the beginning. Based on empirical analysis we observe beta convergence on labour productivity across thirty-one provinces and eight production sectors. Labor productivity across provinces and sectors in China

Table 12
Inequality and labour productivity across provinces robust estimation in China.

Variables	Unconditional model	Conditional model	Conditional model with controls	Conditional model dynamic with controls
$Gini_{t-1}$ (β)	−0.348**	−0.0358	0.0233	−0.00840**
	(0.115)	(0.0332)	(0.0264)	(0.00353)
FDI			0.0152***	0.00974***
			(0.00344)	(0.00121)
HC			−0.341***	−0.0176***
			(0.0944)	(0.00293)
FC			−0.0949***	−0.0375***
			(0.0209)	(0.00145)
Year fixed effects		−0.0119***	0.0242***	0.00198***
		(0.00351)	(0.00596)	(0.000221)
Province fixed effects		1.493***	−2.814***	0.000585**
		(0.441)	(0.701)	(0.000251)
$Growth_{t-1}$				0.373***
				(0.00298)
Constant	−0.426**	0.00	0.00	−3.709***
	(0.155)	(0.00)	(0.00)	(0.436)
Observations	403	403	403	372
Number of groups	31	31	31	31

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

Table 13
Quantile regression of provincial inequality and productivity in China.

Variables	0.1	0.2	0.4	0.5	0.6	0.8	0.9
$Gini_{t-1}$	0.00637	0.0312	−0.0426***	0.0210***	0.0670***	0.0333	−0.0168***
	(0.0464)	(0.0236)	(0.00863)	(0.00292)	(0.00861)	(0.0228)	(0.00426)
FDI	0.00533	−0.0118***	−0.000323	−0.0131***	−0.0175***	−0.0136**	0.000577
	(0.0114)	(0.00327)	(0.00216)	(0.00107)	(0.00314)	(0.00552)	(0.00133)
HC	−0.0311	−0.0209**	0.0108***	−0.00239	0.0330***	0.0381**	0.00145
	(0.0390)	(0.0105)	(0.00373)	(0.00229)	(0.00579)	(0.0155)	(0.00194)
FC	−0.0535	0.00360	−0.00773*	0.00662***	−0.0358***	−0.0190**	−0.00313***
	(0.0348)	(0.00264)	(0.00431)	(0.00245)	(0.00446)	(0.00758)	(0.000616)
Year fixed effects	0.000730	−0.00667***	−0.00574***	−0.00772***	−0.00584***	−0.00770***	−0.00660***
	(0.00538)	(0.000166)	(0.000291)	(0.000190)	(0.000360)	(0.000351)	(7.19e-05)
Province fixed effects	0.0237	−0.0149**	0.00169	−0.000124*	0.000918***	0.00102	−0.000372***
	(0.0174)	(0.00684)	(0.00244)	(6.42e-05)	(0.000191)	(0.000637)	(6.97e-05)
Observations	403	403	403	403	403	403	403
Number of groups	31	31	31	31	31	31	31

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

are eventually moving towards the same steady state. We also find evidence for some variations or asymmetric patterns of convergence by human capital (HC), FDI, industrial concentration (HHI) or inequality (Gini index). Then trends of sigma convergence appear strong across provinces and sectors. Despite bidirectional causality between inequality and growth, impact of inequality on labour productivity is not uniform but more asymmetric.

5. Conclusions and policy recommendations

We have estimated and established unconditional and conditional β convergence and σ convergence in labour productivity empirically across thirty-one provinces and eight production sectors with static and dynamic OLS, GMM and quintile panel data models for years 2003–2019.

There is overwhelming evidence for β convergence among provinces and sectors despite large scale disparity in their economic structures. We enrich the model by extending other control variables including FDI, human capital and income inequality and find even stronger conditional convergence as the explanatory power were increased by adding additional variables in the model. Quintile versions of panel data models show such convergence differ by the level of development of provinces or technological factors across of production. Greater inequality causes more divergence; therefore, China should be encouraged to implement more regionally and sectoral targeted economic policies. The government of China should pay more attention to equality while setting economic policies for achieving convergence in labour productivity, ensuring that more people benefit from economic growth in general.

The effects of FDI on productivity convergence are asymmetric across provinces and sectors. Human capital effects on productivity convergence is asymmetric across provinces. The average impact of human capital on provincial productivity is negative and contributes to convergence, but the effect of human capital varies across provinces as shown in quantile estimations. Meanwhile it was surprising to note that human capital nearly had no effect on sectoral productivity.

CRediT authorship contribution statement

Keshab Bhattarai: Conceptualization, Methodology, Software, Validation, Investigation, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Weiguang Qin:** Validation, Investigation, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

There is no conflict of interest with any party on materials produced in this paper.

Data availability

Data will be made available on request.

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