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An empirical study of openness and convergence in labor productivity in the Chinese provinces

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Abstract Based on the theoretical framework of the Solow growth model, this paper employs a dynamic panel data approach to examine the impact of openness on growth and convergence in labor productivity in the Chinese provinces during the period 1984–2008. The study finds that regional openness has a significantly positive effect on regional growth in labor productivity in the Chinese provinces. When regional heterogeneity and regional openness are accounted for, the study finds fast conditional convergence in labor productivity across the Chinese provinces. As a byproduct, this study also estimates the structural parameters of the aggregate production function in the case of China. In sum, the major findings of this study lend strong support to the claim that openness promotes growth of labor productivity in China.

Keywords Openness · Economic growth · Convergence · Productivity

JEL Classification O47 · O53

1 Introduction

By most standards China's post-1978 economic reforms have been seen as a colossal success. It is widely argued that much of China's economic success in the past three decades is related to the country's ever-increasing openness to foreign trade and inward flows of foreign direct investment (FDI). Since the early 1980s, through a controlled effort to open up the country selectively to trade and FDI, China has gradually transformed itself into a major trading nation in the world.

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The trade to GDP ratio quadrupled from about 9% in 1980 to over 36% in 2000. The country also transformed itself from one with virtually no foreign-invested firms in 1978 to the largest developing-country destination for FDI by 2002 (Wei 2002). In 2002, China surpassed the US with FDI inflows of 53 billion US dollars. In 2004, FDI inflows constituted 7% of gross capital formation. Twenty-eight percent of industrial output was produced by foreign-invested enterprises (FIE's), and over one-fifth of China's tax revenue came from FIE's. Also, more than half (57%) of China's exports were created by FIE's (Zhang 2006).

Although ever-increasing trade openness and inflows of FDI seem to have exerted great impacts on the burgeoning Chinese economy in many important ways, yet the degree of participation in foreign trade varies greatly from one province to another, and FDI inflows are also highly unevenly distributed across different provinces. This is because the opening up was initially limited to two southern provinces (Guangdong and Fujian), and then was gradually extended to other provinces along the coast and then to the inland provinces. In other words, over the three decades, international trade and FDI has been gradually penetrating from the coastal special economic zones (SEZ's) into other coastal areas and inland China. In this paper, by exploiting the large variation in the degree of openness across the Chinese provinces, we investigate the impact of openness on the growth and convergence in labor productivity in the Chinese provinces over the period of 1984–2008. Using a dynamic panel data approach based on the theoretical framework of the Solow growth model, we find that openness has a significant effect on labor productivity growth in the Chinese provinces. When regional heterogeneity and regional openness are accounted for, we find fast conditional convergence in labor productivity across the Chinese provinces. As a byproduct, we also estimate the structural parameters of the aggregate production function in the case of China. In sum, our major findings in this study lend strong support to the claim that openness promotes growth of labor productivity in China.

The rest of this paper is organized as follows. In Sect. 2 we present a literature review. In Sect. 3 we build the dynamic panel data framework needed for our empirical work in later sections. In Sect. 4 we present an introduction to the regression methods used in this study. Section 5 discusses various issues concerning the data and variables. Basic estimation results are presented in Sect. 6. We incorporate human capital into our regression model in Sect. 7. In Sect. 8 we present an interpretation of our empirical results. Finally, Sect. 9 concludes.

2 Literature review

The relationship between openness and economic growth has been the subject of a voluminous literature. Therefore, this brief section of literature review can only intend to cover those previous studies that are the most recent and the most closely related to the present study.

Démurger (2000), in investigating the relation between FDI and growth across 24 Chinese provinces over 1985–1996, estimates a system of equations where both growth and FDI are simultaneously determined. Results show that FDI contributes positively and significantly to GDP growth, and that past GDP growth helps explain FDI. Such a two-way causality between FDI and growth at the national level in China is also found in Zhang (1999). Démurger et al. (2002) work on estimating the separate effects of geographical and policy factors on regional growth in China. They find that both geography and policy have had significant effects on regional growth over different periods in the post-Mao era. The significant role of geography in promoting regional development is also found in Bao et al. (2002). DaCosta and Carroll (2001) find a positive role of trade openness in determining regional growth rates in China. In their study the openness variable also captures the effects of other factors (such as FDI and SEZ's) that promote faster growth in particular regions. Yao and Zhang (2001), by using a panel data framework, find that transportation and openness are two variables that have significant effects on regional income in China. Hu and Owen (2003) point out the widely divergent patterns of regional economic development and varying degrees of openness across the Chinese provinces since the mid-1980s. Their regression analysis suggests that the spillover effects from trade and FDI are highly localized, either within provinces or across regional sub-groupings. Wang and Gao (2003) first construct exogenous components of openness to FDI and trade based on geographic and cultural attributes of Chinese provinces, and then use them to obtain instrumental variable (IV) estimates of the effects of FDI and trade on income and growth. They find positive effects of FDI on both income and growth.

More recently, Zhang (2006) extends some earlier empirical studies on the issue by developing a new framework and providing evidence from panel data of the Chinese provinces. The paper first identifies potential channels through which FDI may positively or negatively affect the Chinese regional economy, and then works on a growth model, in which direct effects and spillovers of FDI are specified. The results suggest that FDI tends to promote income growth, and that this positive growth effect seems to rise over time and to be stronger in the coastal than in the inland regions. Madariaga and Poncet (2007), by using a GMM estimation for dynamic panels, provide a case study of whether FDI promotes economic growth across China. They rely on city-level data to estimate a dynamic panel growth equation, taking into account the issue of spatial interdependence. Their results show that spatial relationships between Chinese cities matter significantly. Estimates suggest that economic growth responds positively to FDI received locally as well as in proximate cities. Ouyang (2009) uses city data from China to examine the extent and mechanisms by which FDI concentrated in China's coastal regions boosts economic growth of inland regions. Unlike Madariaga and Poncet (2007), Ouyang (2009) focuses on coastal-inland spillovers and further stresses the exploration of related spillover channels. Jiang (2011) focuses on how openness affects productivity growth in different regions in China, and examines two effects of openness on regional productivity growth in China: the direct growth effect and the convergence effect. By using a variety of panel data regression techniques, Jiang (2011) shows that the direct growth effect of openness is the main effect while the convergence effect is insignificant.

The findings of the literature above mostly provide evidence to the claim that the opening up of China promotes the country's economic growth. In the current paper, we investigate the impact of openness on the growth and convergence in labor productivity in the Chinese provinces over the period of 1984–2008 by using a dynamic panel data approach based on the theoretical framework of the Solow growth model. Our basic methodology is similar to that of Yao and Zhang (2001), but we employ a wider variety of panel data estimation techniques and use more recent data covering a period up to the year 2008.

3 The model

We follow Mankiw et al. (1992) and Islam (1995) but augment the Solow growth model by including a variable measuring openness. We focus on the model's implications for a panel data regression framework. Assume a Cobb-Douglas production function:

$$Y(t) = K(t)^{\alpha}(B(t)L(t))^{1-\alpha} \tag{1}$$

where $Y(t)$, $K(t)$ and $L(t)$ denote output, physical capital stock and labor force at time t respectively. $L(t)$ grows exogenously at rate n so that $L(t) = L(0)e^{nt}$. $B(t)$ measures the effectiveness of labor at time t, which is in turn composed of two influencing factors that are entered multiplicatively:

$$B(t) = (1 + F(t))^{\mu}A(t) \tag{2}$$

where $A(t)$ grows exogenously at rate g for all economies in all periods so that $A(t) = A(0)e^{gt}$. It is reasonable to assume that we are always able to chip away from $B(t)$ a component $A(t)$ whose growth is exogenous and unaffected by openness.[1]

$F(t)$ is some measure of openness to foreign trade at time t. Openness to foreign trade is assumed to have a positive effect on labor effectiveness for various reasons such as technology spillovers through foreign trade, new technology embodied in imported capital and inputs, and technology induced by strong incentives of domestic producers to innovate when faced with the (bigger) international market, to name but a few. If instead we assume a completely closed economy where $F(t)$ is zero for all time periods, then $B(t)$ reduces to $A(t)$ and this augmented model reduces to the traditional Solow growth model. Defining $\hat{y}(t) \equiv Y(t)/[A(t)L(t)]$, and $\hat{k}(t) \equiv K(t)/[A(t)L(t)]$, we get

$$\hat{y}(t) = (1 + F(t))^{\mu(1-\alpha)}\hat{k}(t)^{\alpha} \tag{3}$$

Starting from some initial point of time t_1 and assuming a constant F throughout $[t_1, +\infty]$, the dynamic equation for $\hat{k}(t)$ is given by

$$\dot{\hat{k}}(t) = s\hat{y}(t) - (n + g + \delta)\hat{k}(t) = s(1 + F)^{\mu(1-\alpha)}\hat{k}(t)^{\alpha} - (n + g + \delta)\hat{k}(t) \tag{4}$$

where, just as in the traditional Solow model, s is the constant saving rate and δ is the constant depreciation rate. Therefore, $\hat{k}(t)$ and $\hat{y}(t)$ converge to their steady-state values $\hat{k}^*$ and $\hat{y}^*$:

[1] We should note that besides technology, $B(t)$ should also capture factors such as resource endowments, institutions, culture and the like.

$$\hat{k}^* = (1+F)^{\mu}\left(\frac{s}{n+g+\delta}\right)^{1/(1-\alpha)}$$
$$\hat{y}^* = (1+F)^{\mu}\left(\frac{s}{n+g+\delta}\right)^{\alpha/(1-\alpha)} \tag{5}$$

Approximating around the steady state, the pace of convergence is given by

$$\frac{d\ln\hat{y}(t)}{dt} = \lambda[\ln\hat{y}^* - \ln\hat{y}(t)] \tag{6}$$

where $\lambda = (n+g+\delta)(1-\alpha)$.[2] Equation (6) implies that

$$\ln\hat{y}(t_2) = (1-e^{-\lambda\tau})\ln\hat{y}^* + e^{-\lambda\tau}\ln\hat{y}(t_1) \tag{7}$$

in which $\tau = (t_2 - t_1)$. Substituting for $\hat{y}^*$ gives

$$\begin{aligned}\ln\hat{y}(t_2) = {} & (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(s) - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\delta) \\ & + e^{-\lambda\tau}\ln y(t_1) + (1-e^{-\lambda\tau})\mu\ln(1+F)\end{aligned} \tag{8}$$

Reformulating Eq. 8 in terms of labor productivity, $y(t) \equiv Y(t)/L(t)$, we get

$$\begin{aligned}\ln y(t_2) = {} & (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(s) - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\delta) + e^{-\lambda\tau}\ln y(t_1) \\ & + (1-e^{-\lambda\tau})\mu\ln(1+F) + (1-e^{-\lambda\tau})\ln A(0) + g(t_2 - e^{-\lambda\tau}t_1)\end{aligned} \tag{9}$$

If we use the following conventional notation of the panel data estimation, we get

$$y_{it} = \gamma y_{i,t-1} + \sum_{j=1}^{3}\beta_j x_{it}^j + \eta_t + u_i + v_{it} \tag{10}$$

where $y_{it} \equiv \ln y(t_2)$, $y_{i,t-1} \equiv \ln y(t_1)$, $x_{it}^1 \equiv \ln(s)$, $x_{it}^2 \equiv \ln(n+g+\delta)$, $x_{it}^3 \equiv \ln(1+F)$, $\gamma \equiv e^{-\lambda\tau}$, $\beta_1 \equiv (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}$, $\beta_2 \equiv -(1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}$, $\beta_3 \equiv (1-e^{-\lambda\tau})\mu$, $u_i \equiv (1-e^{-\lambda\tau})\ln A(0)$, $\eta_t \equiv g(t_2 - e^{-\lambda\tau}t_1)$, and v_{it} is the zero-mean idiosyncratic error that varies across countries and time periods. Equation (9) forms our basic regression framework in later sections.[3]

4 The estimation methods

The panel data specification in (9) is dynamic in nature as the lagged dependent variable appears on the right-hand side of the equation. This renders the pooled OLS estimator and the random effects (RE) estimator biased and inconsistent. However,

[2] See, for example, Barro and Sala-i-Martin (1995) or Romer (2006) for the derivation.

[3] Given the functional specification in (9), we can see that this model does not have much to say about the indirect effect of openness on growth through its impact on capital accumulation because the investment rate is also included as one of the explanatory variables.

the fixed effects (FE) estimator is permissible. Although in this case the FE estimator is inconsistent when the asymptotic properties are considered in the direction of $N \to \infty$, Amemiya (1967) has shown that when the asymptotics are considered in the direction of $T \to \infty$, the FE estimator proves to be consistent and asymptotically equivalent to the Maximum Likelihood Estimator (MLE) (Islam 1995). In a cross-country growth study Islam (1995) has used both this FE estimator and the Minimum Distance (MD) estimator proposed by Chamberlain (1982), but found that there were no significant differences between results of the two estimators. This further justifies the use of the FE estimator in such cases. Following Islam (1995), Yao and Zhang (2001) have also used the same FE method in their growth study of the Chinese provinces. In the analysis of the present paper, however, we will use a variety of panel data estimation methods including the regular FE and FD (first-differencing) methods, an FD 2SLS method, as well as a dynamic panel data GMM method to generate, and compare our regression results.

The FD 2SLS and GMM methods used in this study are based on the sequential exogeneity assumption (see, for example, Wooldridge 2001), which implies that the error term is (taken to be) uncorrelated with the *current and past* (and in certain cases only the *past*) values of the explanatory variables. The model in (10), because of its dynamic nature, necessarily violates the strict exogeneity assumption. However, the sequential exogeneity assumption is applicable in this case. Under the sequential exogeneity assumption, a general approach to estimating Eq. 10 is to first use a transformation to remove the unobserved effect (the u_i term in Eq. 10), and then search for instrumental variables. The FE transformation can be used provided that strictly exogenous instruments are available. For the present study, however, strictly exogenous instruments are difficult to find. Therefore, we will use a 2SLS method based on the FD transformation. First differencing Eq. 10 gives

$$\Delta y_{it} = \gamma \Delta y_{i,t-1} + \sum_{j=1}^{3} \beta_j \Delta x_{it}^j + \Delta \eta_t + \Delta v_{it} \tag{11}$$

where $\Delta y_{it} \equiv y_{it} - y_{i,t-1}$ and so on. Under the sequential exogeneity assumption, we have

$$E(\mathbf{w}_{is}' v_{it}) = \mathbf{0}, \quad s = 1, 2, \ldots, t \tag{12}$$

where $\mathbf{w}_{is} \equiv (y_{i,s-1}, x_{is}^j)$, $j = 1, 2, 3$. Condition (12) implies the orthogonality conditions

$$E(\mathbf{w}_{is}' \Delta v_{it}) = \mathbf{0}, \quad s = 1, 2, \ldots, t - 1. \tag{13}$$

Therefore, at time t we can use $\mathbf{w}_{i,t-1}^o$ as potential instruments for $\Delta \mathbf{w}_{it}$, where $\mathbf{w}_{it}^o \equiv (\mathbf{w}_{i1}, \mathbf{w}_{i2}, \ldots, \mathbf{w}_{it})$. This forms the basis of our panel data approach in this paper. In the various FD 2SLS and GMM estimations presented in Sect. 6 below, we will use subsets of $\mathbf{w}_{i,t-1}^o$ as instrumental variables for (a subset of) $\Delta \mathbf{w}_{it}$ in the FD transformation of Eq. 10, that is, Eq. 11.[4]

[4] An extended GMM method of Blundell and Bond (2000), in which lagged first differences are also used as instruments for the levels equations, should work better than standard first-differenced GMM methods

5 The data and variables

The data are obtained from the officially published *Chinese Statistical Yearbooks* (1984–2009) and *Comprehensive Statistical Data and Materials on 55 Years of New China*. The data comprise the following variables for 29 provinces (including municipalities and autonomous regions) during the period 1984–2008: provincial output, total investment in fixed assets, total population and the population of all working people, total exports and total imports.[5] Series of nominal Gross Regional Product (GRP), GRP indices, and total employed persons (1984–2008) for each province are directly available from the *Chinese Statistical Yearbooks* (1984–2009), so that values of real GRP (1984–2008) for each province are easily obtained. Real per worker output (labor productivity) is calculated as real GRP divided by the number of total employed persons for each province. The provincial investment rate s is calculated as the proportion of the annual investment in fixed assets in the annual provincial GRP, averaged over the concerned time span. The population growth rate n is calculated as the average annual growth rate of the year-end working population over the concerned time span. The openness indicator F is calculated as the ratio of total value of foreign trade (exports plus imports, converted to RMB yuan) to the corresponding regional GRP of the same year, averaged over the concerned time span. We set $(g + \delta)$ equal to 0.07 and assume that this value remains constant for all provinces in all years.

The assumption of a constant $(g + \delta)$ may not be entirely realistic, but just like in earlier studies, we could not directly estimate the actual values of g and δ. For China, Jefferson et al. (1992) estimate a production function with capital, labor, and intermediate inputs and find a rate of technological change of about 0.02 for Chinese state-owned industry and of about 0.04 for Chinese collective industry. These results may serve as a first approximation of g, though human capital accumulation is not taken into account and the focus is on technological change in industries rather than in the aggregate economy.[6] According to Gundlach (1997), another approximation of g may be derived from the estimates for countries (or regions) such as South Korea and Taiwan, which experienced similar growth rates as Mainland China in the 1980s. Young (1995) finds average rates of total factor productivity growth of 0.016 for South Korea and of 0.024 for Taiwan.[7] These results suggest that the standard parameterization of g of 0.02 is also reasonable in the case of China.

Footnote 4 continued
when the variables are highly persistent so that lagged values are only weakly correlated with subsequent first differences. However, we have not opted for the use of extended GMM method of Blundell and Bond (2000) in this analysis mainly because the series of the variables in our regressions are not very highly persistent and the Arellano-Bond GMM regressions currently used in the analysis are shown to be valid by passing the related Sargan and AR tests.

[5] Owing to missing data Chongqing and Hainan are not included in our sample.

[6] See Gundlach (1997). In this and the next paragraph, we mainly follow Gundlach (1997) for a discussion of the estimated values of the rate of technological progress and the rate of depreciation.

[7] Compared with Jefferson et al. (1992), Young (1995) takes account of human capital accumulation and focuses on the aggregate economy instead of individual industries.

We cannot directly measure the depreciation rate because data on the stock of physical capital and its depreciation are not directly available for China. However, according to Maddison (1987), the average figure of the ratio of depreciation to GDP is about 0.1 for industrialized countries. Therefore, the depreciation rate can be calculated once the capital-output ratio is known since $\delta = (D/Y)/(K/Y)$. Gundlach (1997) argues that for leading industrial countries such as the United States, the capital-output ratio is about 3, so δ would be about 0.03, but for developing countries, it is reasonable to assume a smaller capital output ratio. Thus, for a capital-output ratio of 2, δ will be 0.05. It is possible that the actual capital-output ratio may be even lower than 2 in developing countries, but the ratio of depreciation to GDP may also be lower than 0.1. On balance, therefore, we follow Gundlach (1997) and assume a depreciation rate of 0.05 for the Chinese provinces.[8]

The total period of 1984–2008 is divided into six 4-year spans: 1984–1988, 1988–1992, 1992–1996, 1996–2000, 2000–2004 and 2004–2008. Values of explanatory variables s, n, and F are calculated as the averages over the corresponding spans. With this setup, the transitory error terms are four calendar years apart and hence may be less likely serially correlated than they would be in an annual data setup (Islam 1995). To account for the time intercept in Eq. 10, We use five time dummy variables respectively for the five time spans other than 1984–1988.

6 Estimation results

Table 1 summarizes major regression results from various estimation methods. For brevity, we have not reported the estimated intercepts (the common intercept and the estimated coefficients on the time dummy variables). Although the RE estimation produces biased and inconsistent results, we nevertheless include it in the table for a comparison purpose. The second and third regressions are the regular FE and FD estimations. The fourth regression is a 2SLS estimation based on the FD transformation. In this FD 2SLS regression, we use lags of the explanatory variables in the periods $(t-1)$ and $(t-2)$ (i.e. $\ln y_{i,t-2}$, $\ln y_{i,t-3}$, $\ln s_{i,t-1}$, $\ln s_{i,t-2}$, $\ln(n_{i,t-1} + 0.07)$, $\ln(n_{i,t-2} + 0.07)$, $\ln(1 + F_{i,t-1})$ and $\ln(1 + F_{i,t-2})$) as instruments for the *first-differenced* form of Eq. 10, i.e. Eq. 11, at period t. The latter three regressions use a panel data GMM method—the Arellano-Bond dynamic estimation (Arellano and Bond 1991), in which *all possible* lags of the dependent and independent variables are used as instruments for the first-differenced equation (i.e. Eq. 11). The regression GMM (1) simply takes the explanatory variables (other than $\ln y_{i,t-1}$) as exogenous and uses all lags of the dependent variable $\ln y_{it}$ up to the period $(t-3)$

[8] Given this, it then can be shown that all major regression results in this study are not sensitive to the chosen value of the depreciation rate if it is within the interval [0.03, 0.07]. Unlike Gundlach (1997), some other studies alternatively assume or estimate a different depreciation rate for each of the Chinese provinces. However, we do not follow this approach in the present study because this approach confronts us with an immediately related issue, i.e. the possibility of time-varying depreciation rates for any single province, which will take us too far afield given the main scope of the present study.

Table 1 Unrestricted model without human capital

Dependent variable: ln y_{it}
Sample: 29 Chinese provinces, 1984–2008

Major variables	RE	FE	FD	FD 2SLS	GMM (1)	GMM (2)	GMM (3)
ln $y_{i,t-1}$	0.962* (0.015)	0.715* (0.051)	0.528* (0.063)	0.501* (0.154)	0.591* (0.176)	0.658* (0.061)	0.710* (0.072)
ln s_{it}	0.105* (0.033)	0.165* (0.037)	0.201* (0.037)	0.263* (0.090)	0.177* (0.035)	0.202* (0.037)	0.183* (0.039)
ln(n_{it} + 0.07)	–0.337* (0.030)	–0.296* (0.028)	–0.271* (0.026)	–0.121 (0.075)	–0.290* (0.037)	–0.277* (0.025)	–0.291* (0.032)
ln(1 + F_{it})	0.177* (0.050)	0.225* (0.075)	0.314* (0.086)	0.424 (0.245)	0.372* (0.111)	0.360* (0.089)	0.327* (0.100)
No. obs	174	174	145	116	116	116	116
Implied λ	0.010	0.084	0.160	0.173	0.131	0.105	0.086

Robust standard errors are in parentheses. The * denotes "significant at the 5% level". For the lagged dependent variable it means "significantly lower than unity at the 5% level" while for the other explanatory variables it means "significantly different from zero at the 5% level". Results of the GMM regressions are one-step results. For GMM (1), GMM (2) and GMM (3), the p-values associated with the Sargan test of over-identifying restrictions are 0.113, 0.108 and 0.152, respectively. The p-values associated with the Arellano-Bond test that average autocovariance in residuals of order one is 0 (H_0: no autocorrelation) are 0.445, 0.160 and 0.129, respectively. The p-values associated with the Arellano-Bond test that average autocovariance in residuals of order two is 0 (H_0: no autocorrelation) are 0.528, 0.487 and 0.545, respectively

as instruments for Eq. 11 at period t. The regression GMM (2) takes the explanatory variables $\ln s_{it}$, $\ln(n_{it} + 0.07)$ and $\ln(1 + F_{it})$ as predetermined and uses all lags of them up to the period $(t - 1)$ and all lags of the dependent variable $\ln y_{it}$ up to the period $(t - 3)$ as instruments for Eq. 11 at period t. The regression GMM (3) instead takes the explanatory variables $\ln s_{it}$, $\ln(n_{it} + 0.07)$ and $\ln(1 + F_{it})$ as endogenous and uses all lags of them up to the period $(t - 2)$ and all lags of the dependent variable $\ln y_{it}$ up to the period $(t - 3)$ as instruments for Eq. 11 at period t.[9]

The RE regression in Table 1 has produced a relatively high estimated coefficient on $\ln y_{i,t-1}$. This is because this regression does not control for the time-constant province heterogeneity.[10] Compared with the RE regression, all the other regressions produce estimated coefficients on $\ln y_{i,t-1}$ that are much lower and all significantly lower than unity. Therefore, the seven regressions in Table 1 all suggest conditional convergence in labor productivity across the 29 provinces over the sample period. The estimated coefficients on the other variables $\ln s_{it}$, $\ln(n_{it} + 0.07)$ and $\ln(1 + F_{it})$ all have the expected signs, and they are significant at the 5% level in the regressions with very few exceptions. Specifically, the estimated coefficients on $\ln(1 + F_{it})$ are significantly positive at the 5% level (with one exception in the FD 2SLS regression[11]) and practically large, suggesting a large positive effect of regional openness on regional labor productivity growth in the Chinese regions. Finally, the implied values of the rate of convergence λ are entered in the last row, which are directly calculated from the estimates of the coefficient on $\ln y_{i,t-1}$.

We need to obtain estimates of the structural parameter α in the aggregate production function. Seeing that the coefficients on ln(s) and ln(n + g + δ) are equal in magnitude and opposite in sign in Eq. 9, we now combine the two explanatory variables $\ln s_{it}$ and $\ln(n_{it} + 0.07)$ into a single explanatory variable $[\ln s_{it} - \ln(n_{it} + 0.07)]$ and run regressions parallel to those in Table 1.[12] Results of these restricted regressions are summarized in Table 2. The estimated coefficients on the combined variable $[\ln s_{it} - \ln(n_{it} + 0.07)]$ all have the expected positive sign and are all very significant at the 5% level in the seven regressions. Comparing regressions in Table 2 with those in Table 1, we see that in most cases putting the restriction on the regressions does not alter the estimated values of the coefficients on the other explanatory variables in any important ways. Again, from Table 2, we see that $\ln(1 + F_{it})$ has a large positive partial effect on the dependent variable. Once we have obtained the estimates of the coefficients on the explanatory variables, we can then calculate the implied values of the rate of convergence λ and the output elasticity of capital α in the aggregate production function. It should be

9 Taking an explanatory variable as endogenous means that we assume it to be correlated with the current error term while taking it as predetermined means that we instead assume it to be uncorrelated with the current error term. We run different variants of the regression here mainly for a comparison purpose.

10 Even in this RE regression the estimated coefficient on $\ln y_{i,t-1}$ is significantly lower than unity at the 5% level, suggesting conditional convergence across the 29 Chinese provinces over the sample period.

11 The corresponding p-value of this estimate is 0.086.

12 However, the Wald test rejects the null hypothesis that the coefficients on ln(s) and $\ln(n + g + \delta)$ are equal in value but opposite in sign in most of the previous regressions in Table 1. This renders the estimation of the parameter α here based on the results in Table 2 less meaningful.

Table 2 Restricted model without human capital

Dependent variable: ln y_{it}
Sample: 29 Chinese provinces, 1984–2008

Major variables	RE	FE	FD	FD 2SLS	GMM (1)	GMM (2)	GMM (3)
ln $y_{i,t-1}$	0.943* (0.017)	0.690* (0.052)	0.503* (0.062)	0.612* (0.113)	0.451* (0.231)	0.633* (0.066)	0.660* (0.078)
[ln s_{it} − ln(n_{it} + 0.07)]	0.240* (0.023)	0.247* (0.021)	0.248* (0.021)	0.200* (0.052)	0.236*(0.029)	0.253* (0.021)	0.246* (0.025)
ln(1 + F_{it})	0.209* (0.055)	0.273* (0.074)	0.338* (0.085)	0.316 (0.191)	0.485* (0.113)	0.434* (0.088)	0.420*(0.100)
No. obs	174	174	145	116	116	116	116
Implied λ	0.015	0.093	0.172	0.123	0.199	0.114	0.104
Implied α	0.808	0.443	0.333	0.186	0.301	0.408	0.420

Robust standard errors are in parentheses. The * denotes "significant at the 5% level". For the lagged dependent variable it means "significantly lower than unity at the 5% level" while for the other explanatory variables it means "significantly different from zero at the 5% level". Results of the GMM regressions are one-step results. For GMM (1), GMM (2) and GMM (3), the p-values associated with the Sargan test of over-identifying restrictions are 0.105, 0.136 and 0.145, respectively. The p-values associated with the Arellano-Bond test that average autocovariance in residuals of order one is 0 (H_0: no autocorrelation) are 0.397, 0.212 and 0.187, respectively. The p-values associated with the Arellano-Bond test that average autocovariance in residuals of order two is 0 (H_0: no autocorrelation) are 0.445, 0.434 and 0.432, respectively

noted that the results of the GMM regressions in Tables 1 and 2 are the one-step results (also the default results reported by the software) and all these GMM regressions have passed the Sargan test of over-identifying restrictions and the Arellano-Bond autocorrelation test of the residuals (orders one and two) at the 5% significance level.[13] For Table 2, therefore, if we take the latter two regressions, GMM (2) and GMM (3), as the conceptually soundest methods, and compare results of these two regressions with those of the FE regression, which method is also justifiable, we may conclude that, according to our regression results, the empirically implied rate of convergence λ is about 0.10, and the implied output elasticity of capital α is about 0.42.

7 Inclusion of human capital

We wonder what happens if human capital is incorporated into our analysis. To see this, we now assume[14]

$$Y(t) = K(t)^{\alpha} M(t)^{\varphi} (B(t)L(t))^{1-\alpha-\varphi} \tag{14}$$

where M is the stock of human capital, and all other variables are defined as before. Let h be the fraction of income invested in human capital. The evolution of the economy is now determined by

$$\begin{aligned} \dot{\hat{k}}(t) &= s\hat{y}(t) - (n+g+\delta)\hat{k}(t) \\ \dot{\hat{m}}(t) &= h\hat{y}(t) - (n+g+\delta)\hat{m}(t) \end{aligned} \tag{15}$$

where $\hat{m} = M/(AL)$, and where we have assumed human capital depreciates at the rate δ too. We assume $\alpha + \varphi < 1$, which implies there are decreasing returns to all capital. Eq. 15 implies that the economy converges to a steady state defined by

$$\begin{aligned} \hat{k}^* &= (1+F)^{\mu} \left(\frac{s^{1-\varphi} h^{\varphi}}{n+g+\delta} \right)^{1/(1-\alpha-\varphi)} \\ \hat{m}^* &= (1+F)^{\mu} \left(\frac{s^{\alpha} h^{1-\alpha}}{n+g+\delta} \right)^{1/(1-\alpha-\varphi)} \end{aligned} \tag{16}$$

Approximating around the steady state, the speed of convergence is given by

$$\frac{d \ln \hat{y}(t)}{dt} = \lambda [\ln \hat{y}^* - \ln \hat{y}(t)] \tag{17}$$

where $\lambda = (n+g+\delta)(1-\alpha-\varphi)$.[15] Following the same procedure as before, we get

[13] See the notes below the tables for the details.

[14] Here we still follow the basic procedure of Mankiw et al. (1992) and Islam (1995) except that we include an openness variable in the model.

[15] See, for example, Barro and Sala-i-Martin (1995) or Romer (2006) for the derivation.

$$
\begin{aligned}
\ln \hat{y}(t_2) - \ln \hat{y}(t_1) = {} & (1 - e^{-\lambda\tau}) \frac{\alpha}{1 - \alpha - \varphi} \ln(s) + (1 - e^{-\lambda\tau}) \frac{\varphi}{1 - \alpha - \varphi} \ln(h) \\
& + (1 - e^{-\lambda\tau}) \mu \ln(1 + F) - (1 - e^{-\lambda\tau}) \frac{\alpha + \varphi}{1 - \alpha - \varphi} \ln(n + g + \delta) \\
& - (1 - e^{-\lambda\tau}) \ln \hat{y}(t_1)
\end{aligned} \tag{18}
$$

Reformulating Eq. 18 in terms of labor productivity yields

$$
\begin{aligned}
\ln y(t_2) = {} & (1 - e^{-\lambda\tau}) \frac{\alpha}{1 - \alpha - \varphi} \ln(s) + (1 - e^{-\lambda\tau}) \frac{\varphi}{1 - \alpha - \varphi} \ln(h) \\
& - (1 - e^{-\lambda\tau}) \frac{\alpha + \varphi}{1 - \alpha - \varphi} \ln(n + g + \delta) + (1 - e^{-\lambda\tau}) \mu \ln(1 + F) \\
& + e^{-\lambda\tau} \ln y(t_1) + (1 - e^{-\lambda\tau}) \ln A(0) + g(t_2 - e^{-\lambda\tau} t_1)
\end{aligned} \tag{19}
$$

Comparing Eqs. 19 with 9 earlier, we see that Eq. 19 now includes the term $\ln(h)$ as one additional explanatory variable.

The major problem with the estimation based on Eq. 19 is that, in contrast to flow measures of physical capital formation such as the investment rate, direct flow or stock measures of human capital formation are generally unavailable. In fact, measures of human capital have always been a weak spot in growth empirics. Mankiw et al. (1992) have provided a very good discussion of the problems involved in this regard. In our following regressions, we will use an indirect flow measure of human capital formation: the number of students enrolled in secondary education divided by the working population. This variable (variable h) is expected to proxy for investment in human capital. Schooling rates as a measure of investment in human capital have been used in recent international cross-section studies of the empirics of growth (Gundlach 1997). Needless to say, the schooling rate is a rather coarse measure of human capital formation. The general idea behind this measure is that variations in the fraction of the population devoted to formal education reflect variations in investment in human capital. Schooling rates at higher levels of education may as well be candidate measures of rates of investment in human capital. For example, data on schooling rates at college-level educational institutions are generally available for the Chinese provinces, but since the types of college-level educational institutions and the quality of the education they provide are much more diversified across different provinces, it is likely that schooling rates at higher levels of education are less reliable proxies for the rate of investment in human capital than schooling rates at the secondary-school level. We may also come up with alternative ways of measuring human capital investment. For example, total income of all professional teachers as a share of the provincial GRP might as well be a proxy for the rate of human capital investment because the teacher's income is supposed to be commensurate with the teaching workload, which in turn proxies for aimed results of education. However, owing to missing data, the use of this variable as a measure of the rate of human capital investment is not feasible for our analysis in this paper.

Another way of studying the contribution of human capital accumulation to (the growth of) per capita income is to focus on the stock of human capital instead of on the flow of human capital. From our model above, it is easy to show that

$$\begin{aligned}\ln y(t_2) = {} & (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(s) + (1-e^{-\lambda\tau})\frac{\varphi}{1-\alpha}\ln(\hat{m}^*) + (1-e^{-\lambda\tau})\mu\ln(1+F) \\ & - (1-e^{-\lambda\tau})\frac{\alpha}{1-\alpha}\ln(n+g+\delta) + e^{-\lambda\tau}\ln y(t_1) \\ & + (1-e^{-\lambda\tau})\ln A(0) + g(t_2 - e^{-\lambda\tau}t_1) \qquad (20)\end{aligned}$$

where $\hat{m}^*$ is the steady-state level of human capital determined by (16). Islam (1995) and Gundlach (1997) have run regressions based on Eq. 20. Islam (1995) uses the variable *HUMAN*, which is supposed to provide information on schooling at all levels, as a direct measure of the stock of human capital. Gundlach (1997) uses publications per worker (*PUBL*) as a measure of the stock of human capital. Gundlach (1997) argues that the provincial supply of written information is correlated with the provincial quantity of human capital. Since the amount of written information is likely dominated by newspapers, *PUBL* will more or less reflect the consumption of newspapers per worker at the provincial level. Therefore, this measure may reflect differences in literacy rates across Chinese provinces, which, in turn, may be more plausible measures of exogenous inter-provincial differences in human capital than the reported schooling rates. However, because of missing and inconsistent data on provincial publications during a sample period as long as 24 years (1984–2008), in this paper we cannot use this variable as a measure of the level of human capital and run regressions based on Eq. 20. Therefore, in this section, we will use the aforementioned schooling rate of secondary education (the number of students enrolled in secondary education divided by the working population, averaged over each corresponding time span) as a proxy variable for the rate of investment in human capital, and run regressions based on Eq. 19.

Regression results are summarized in Table 3 (unrestricted regressions parallel to those in Table 1) and Table 4 (restricted regressions parallel to those in Table 2).[16] Specifically, in all the regressions in Tables 3 and 4, the openness variable $\ln(1 + F_{it})$ exhibits a large positive effect on the dependent variable. For the unrestricted regressions in Table 3, the estimated coefficients on $\ln h_{it}$ all have the expected positive sign (with only one exception in the FD 2SLS regression), but those from the latter four regressions are insignificant while those from the first three regressions are significant at the 5% level. Eyeballing Tables 1 and 3, we see that the inclusion of $\ln h_{it}$ does not substantially change the estimated values of the coefficients on the other variables $\ln y_{i,t-1}$, $\ln s_{it}$, $\ln(n_{it} + 0.07)$ and $\ln(1 + F_{it})$. In the restricted regressions in Table 4, the estimated coefficients on $[\ln s_{it} - \ln(n_{it} + 0.07)]$ and $[\ln h_{it} - \ln(n_{it} + 0.07)]$ all have the expected positive sign, and are significant at the 5% level (with few exceptions). Comparing results in Tables 2 and 4, we see that the inclusion of $[\ln h_{it} - \ln(n_{it} + 0.07)]$ does not substantially change

16 The GMM regressions in Tables 3 and 4 also pass the Sargan test and the Arellano-Bond autocorrelation test of the residuals (orders one and two) at the 5% significance level. See the notes below the tables for the details.

Table 3 Unrestricted model including human capital

Dependent variable: ln y_{it}
Sample: 29 Chinese provinces, 1984–2008

Major variables	RE	FE	FD	FD 2SLS	GMM (1)	GMM (2)	GMM (3)
ln $y_{i,t-1}$	0.953* (0.016)	0.671* (0.052)	0.465* (0.064)	0.511* (0.209)	0.741* (0.195)	0.628* (0.061)	0.664* (0.070)
ln s_{it}	0.108* (0.033)	0.138* (0.037)	0.177* (0.037)	0.261* (0.095)	0.165* (0.036)	0.190* (0.033)	0.186* (0.036)
ln h_{it}	0.051* (0.024)	0.091* (0.033)	0.138* (0.040)	–0.010 (0.139)	0.026 (0.055)	0.027 (0.031)	0.005 (0.033)
ln(n_{it} + 0.07)	–0.335* (0.029)	–0.292* (0.027)	–0.247* (0.026)	–0.122 (0.077)	–0.308* (0.045)	–0.284* (0.023)	–0.297* (0.029)
ln(1 + F_{it})	0.191* (0.051)	0.260* (0.074)	0.357* (0.084)	0.405 (0.359)	0.307* (0.130)	0.382* (0.084)	0.358* (0.095)
No. obs	174	174	145	116	116	116	116
Implied λ	0.012	0.100	0.191	0.168	0.075	0.116	0.102

Robust standard errors are in parentheses. The * denotes "significant at the 5% level". For the lagged dependent variable it means "significantly lower than unity at the 5% level" while for the other explanatory variables it means "significantly different from zero at the 5% level". Results of the GMM regressions are one-step results. For GMM (1), GMM (2) and GMM (3), the *p*-values associated with the Sargan test of over-identifying restrictions are 0.107, 0.104 and 0.125, respectively. The *p*-values associated with the Arellano-Bond test that average autocovariance in residuals of order one is 0 (H_0: no autocorrelation) are 0.248, 0.181 and 0.153, respectively. The *p*-values associated with the Arellano-Bond test that average autocovariance in residuals of order two is 0 (H_0: no autocorrelation) are 0.610, 0.494 and 0.534, respectively

Table 4 Restricted model including human capital

Dependent variable: ln y_{it}
Sample: 29 Chinese provinces, 1984–2008

Major variables	RE	FE	FD	FD 2SLS	GMM (1)	GMM (2)	GMM (3)
ln $y_{i,t-1}$	0.935* (0.017)	0.653* (0.050)	0.492* (0.059)	0.625* (0.122)	0.154* (0.281)	0.664* (0.061)	0.634* (0.070)
$[\ln s_{it} - \ln(n_{it} + 0.07)]$	0.188* (0.026)	0.164* (0.030)	0.157* (0.032)	0.228* (0.066)	0.125* (0.051)	0.239* (0.029)	0.242* (0.031)
$[\ln h_{it} - \ln(n_{it} + 0.07)]$	0.088* (0.022)	0.109* (0.029)	0.108* (0.030)	–0.047 (0.079)	0.101* (0.035)	0.035 (0.028)	0.030 (0.030)
$\ln(1 + F_{it})$	0.219* (0.054)	0.285* (0.071)	0.334* (0.082)	0.289 (0.199)	0.578* (0.131)	0.418* (0.079)	0.478* (0.094)
No. obs	174	174	145	116	116	116	116
Implied λ	0.017	0.107	0.177	0.118	0.468	0.102	0.114
Implied α	0.551	0.265	0.203	–	0.117	0.392	0.379
Implied ϕ	0.258	0.176	0.140	–	0.094	0.057	0.047

Robust standard errors are in parentheses. The * denotes "significant at the 5% level". For the lagged dependent variable it means "significantly lower than unity at the 5% level" while for the other explanatory variables it means "significantly different from zero at the 5% level". Results of the GMM regressions are one-step results. For GMM (1), GMM (2) and GMM (3), the p-values associated with the Sargan test of over-identifying restrictions are 0.146, 0.116 and 0.143, respectively. The p-values associated with the Arellano-Bond test that average autocovariance in residuals of order one is 0 (H_0: no autocorrelation) are 0.380, 0.157 and 0.210, respectively. The p-values associated with the Arellano-Bond test that average autocovariance in residuals of order two is 0 (H_0: no autocorrelation) are 0.591, 0.445 and 0.444, respectively

the estimated coefficients on ln $y_{i,t-1}$ and $\ln(1 + F_{it})$.[17] Implied values of the rate of convergence λ and the structural parameters of the production function α and φ are also entered in Table 4. Unfortunately, owing to the rather coarse measure of human capital investment, we do not expect to obtain very precise estimates of the parameters.

8 Interpretation of the empirical results

We should note that in our empirical analysis, the openness variable captures not only the effects of openness to foreign trade, but also the spillover effects of FDI inflows. It is mainly because of missing data on FDI inflows for some provinces during the early years that we have been forced to limit ourselves to the use of the trade-output ratio as a proxy variable for the degree of openness to foreign trade/FDI. Our major finding is that regional openness has a significantly positive effect on regional labor productivity growth in China. There are several (interrelated) potential channels through which trade and FDI may have impacts on regional labor productivity growth in China.

First,[18] greater openness of a province means greater exposure of the province to new products that are imported or brought in by foreign firms that directly invest in the province. The imitation of new products is an important mechanism of technology transmission. This imitation may improve domestic technology and result in a spillover-enhancing productivity in domestic firms. Second, competition may generate spillovers. Incoming multinational companies may foster competition. New competition faced by domestic firms compels them to innovate. Greater competition improves productivity. Third, by its very nature, FDI may bring into the host economy special resources such as management skills, access of skilled labor to international production networks, and established brand names. Fourth, exports spillovers are also a source of productivity gain. Exporting involves fixed costs in establishing distribution networks, creating transport infrastructure, learning about consumer tastes, etc. Domestic firms learn from multinationals in implementing exporting strategies. Collaboration and imitation lower the fixed costs of exporting and help domestic firms to penetrate new markets. Fifth, vertical spillovers are another important channel through which productivity gains are realized. FIE's can increase demand for inputs produced by local upstream suppliers and thereby spread technology and management skills to domestic firms (Rodriguez-Clare 1996). Spillovers may also take place through the acquisition of human capital from foreign firms. Multinational enterprises demand relatively highly skilled labor and invest in technology and staff training.[19] As a result, labor turnover from

[17] However, in most of the unrestricted regressions in Table 3, the Wald test rejects the null hypothesis that the sum of the coefficients on $\ln(s)$ and $\ln(h)$ are equal to the coefficient on $\ln(n + g + \delta)$ in value but opposite in sign. This renders the estimation of the parameters α and φ here based on the results in Table 4 less meaningful.

[18] This paragraph draws on Madariaga and Poncet (2007)'s summary of Greenaway and Görg (2004)'s discussion of the issue.

[19] By the end of 2004, FIE's employed 23 million Chinese, comprising about 10% of total manufacturing employment.

multinational enterprises to local firms can generate productivity improvement in the local firms. Moreover, openness to trade and FDI seems to bring extra gains to China by facilitating its transition from a centrally planned economy to a market-oriented economy since the early 1980s. Ever-increasing openness helps to introduce a market-oriented institutional framework and contributes to changes in the ownership structure toward privatization by promoting competition and facilitating reforms in state-owned enterprises.

We should also argue that the provincial economic environment plays an important role in facilitating provincial income or productivity growth. Differences in income or productivity growth are fundamentally related to differences in the underlying economic environment across the Chinese provinces. This so-called economic environment is in turn determined by the institutions and government policies. A favorable economic environment gets the price system right so that individuals capture the social returns to their actions as private returns. The ideal measure of the economic environment would thus quantify the wedge between the private return to productive activities and the social return to such activities (Hall and Jones 1999). However, in practice, we do not have a usable quantification of wedges between private and social returns. As a result we must construct proxy variables for the economic environment. We argue that provincial openness to international activities is an acceptable proxy for the provincial economic environment. Policies and practices concerned with international activities such as foreign trade and FDI are sensitive indexes of the economic environment. To some extent, regarding the interpretation of our empirical results, we do not attempt to make a very clear-cut distinction in this paper between effects of openness as a general proxy variable for the economic environment and effects of openness coming from, say, facilitated technology spillovers due to freer trade and FDI inflows.

9 Concluding remarks

In this paper we empirically investigate the relationship between regional openness and regional labor productivity growth across 29 Chinese provinces over the period 1984–2008. We also examine whether there is conditional convergence in labor productivity across the provinces. To tackle these issues, we have applied a variety of panel data estimations on the basis of the theoretical framework of the Solow growth model. Our regression results show that regional openness has a significantly positive and large effect on regional labor productivity growth. Also, when regional openness is controlled for in our regressions, we find fast conditional convergence in labor productivity across the 29 Chinese provinces over 1984–2008.

This paper contributes to the growth literature in three aspects. First, the empirical analysis of this paper improves our understanding of the role of openness in regional growth of the Chinese regions. Compared with literature using cross section methods that paid little attention to the potential endogeneity problem of the explanatory variables when estimating the partial effect of openness, the panel data methods employed in this paper greatly mitigate, if not completely eliminate, the potential endogeneity problem. The main findings of this study lend strong support to the claim that openness promotes growth in China. Second, this paper contributes to the literature on openness and growth by presenting evidence from regions within a single country. It complements evidence from cross-country growth studies, where omitting underlying explanatory variables usually pose a more serious problem in the regressions. Third, this paper has made an effort to incorporate human capital into the analysis. We have shown that regional human capital accumulation has an expected positive effect on regional labor productivity growth in the Chinese provinces.

An investigation into how openness affects underlying factors shaping the growth of labor productivity, such as institutions or structural changes of the regional economy, would provide more insights into the mechanisms through which openness may exert effects on labor productivity growth. Further studies in this direction are indeed on our agenda.

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