Growth convergence and local steady states across Chinese prefectures / Frattini, F.; Nicolli, F.; Prodi, G.. - In: APPLIED ECONOMICS LETTERS. - ISSN 1350-4851. - 24:8(2017), pp. 563-566. [10.1080/13504851.2016.1210763]

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Journal:	*Applied Economics*
Manuscript ID	AEL-2016-0212.R1
Journal Selection:	Applied Economics Letters incorporating Applied Financial Economics Letters
Date Submitted by the Author:	08-Jun-2016
Complete List of Authors:	Frattini, Federico; University of Ferrara, Department of Economics and Management Nicolli, Francesco; National Research Council, Research Institute on Sustainable Economic Growth; University of Ferrara, Department of Economics and Management Prodi , Giorgio; University Ferrara, Department of Economics and Management
JEL Code:	O49 - Other < O4 - Economic Growth and Aggregate Productivity < O - Economic Development, Technological Change, and Growth, O53 - Asia including Middle East < O5 - Economywide Country Studies < O - Economic Development, Technological Change, and Growth
Keywords:	China, convergence, foreign direct investments, patents

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This paper investigates how economic growth paths diverge across Chinese prefectural cities. Based on the conditional convergence hypothesis, the analysis includes inward foreign direct investments and patent applications to the European Patent Office as additional proxies of steady-state income levels and allows the convergence parameter to vary across groups. The results show that within-convergence rates are different across groups, but growth drivers positively affect both intraregional and interregional catching up.

Keywords: China; convergence; foreign direct investments; patents

Subject classification codes: O49; O53

1. Introduction

An impressive long-term growth process has produced sizable regional income disparities in China. Economic growth increased in the Coastal area first, fostered by a strategy of regulated opening and transition (Naughton 2007). Since the late-80s, Inward Foreign Direct Investments (IFDI) have made it possible to import physical capital and technologies, as well as develop indigenous technological capabilities (Fu 2008). Innovation activities actually began rising the next decade, mostly clustering around initial locations (Fan 2014).

A consolidated strand of literature has found a significant positive relationship between IFDI and economic growth in China, whose intensity positively depends on human capital and negatively on technological gaps (Li and Liu 2005). Following on from this evidence but using an alternative approach to usual simultaneous-equation modelling, this letter investigates how IFDI and Knowledge Stocks (KS) generated by indigenous innovation activities structurally affect the pace of regional growth in China.

More precisely, differences in both IFDI and KS endowments are expected to participate in setting interregional disparities and, therefore, differentiating the development process on a local basis. The empirical analysis tests this hypothesis in a model of conditional convergence that considers three periods and prefectural cities to address a proper variability within and across groups.

2. Development drivers and regional disparities in China

Differences in technological capabilities are major determinants of income gaps across countries. Therefore, latecomers can take the most advantage of IFDI as a source of additional and more recent technologies (Lall 1992). When successfully implemented — as in China — policy actions to attract IFDI are able to boost economic growth and foster new capabilities at a local level (Naughton 2007). As a side effect, however, clustering processes can strengthen structural disparities within countries.

The Chinese national government started systematically taking on regional gaps in 1999 with the "Go-West Strategy". Before 2004, this kind of initiative had defined three regions of coordinated development in addition to the Coastal area (Li and Wu 2012). Paces of growth should coherently differ among the regions, and income levels should converge faster within, rather than across, regions. Furthermore, fast growth and structural change continue shaping the development paths, so that geography and history together make the convergence paces local.

3. Testing convergence to local steady states

This paper presents an empirical test based on an endogenous growth model. This framework usually considers catching up as conditional on the net accumulation of physical s_{it}/d_{it} and human h_i capital in addition to the initial income level y_{i0} (Barro and Sala-I-Martin 2004). There is room, however, for introducing other drivers like IFDI f_{it} and indigenous KS k_{it}. Moreover, the model lets the convergence parameter vary over time τ_t and regions ρ_i as follows:

$$\ln(y_{it}/y_{i0})=b_{y\tau\rho}(1+\tau_t\times\rho_i)\ln(y_{i0})+b_s\ln(s_{it})+b_d\ln(d_{it})+b_h\ln(h_{it})+b_f\ln(f_{it})+b_k\ln(k_{it})+u_{it} \quad (1)$$

The literature usually considers 31 provinces for which most statistics since the late-70s are available. Nonetheless, such an administrative level is excessively broad to provide proper variability, and the analysis focuses here on prefectures. All data but KS come from China Data On Line (CDOL), which collects yearly statistics for most prefectural cities in China from 1996 onwards. After excluding incomplete records, the dataset consists of 260 individuals among 345 total, grouped in East (87), Midland (81), Northeast (33) and West (59). The analysis also considers time through splitting records into three five-year spans from 1996 to 2010. Therefore, y_{i0} and y_{it} are GDP per capita at the first and last year in each period, respectively, while the other explanatory variables enter the model as yearly period averages (Table 1).

[Table 1 near here]

In particular, the amount of domestic and foreign investments in fixed assets over GDP easily function as proxies of saving rate and IFDI respectively. The population growth rate is instead augmented by the obsolescence rate calibrated in Mankiw, Romer, and Weil (1992) to proxy the depreciation rate of physical capital. Then, the enrolment in secondary school approximates human capital as common in growth empirics since Barro and Lee (1994). Here, it is calculated as the number of students enrolled in secondary school over population.

KS finally is a common measure built on patent counts (Popp 2002), but CDOL unfortunately does not collect prefectural patent information. As an alternative, the analysis refers to patent applications from Chinese applicants to the European Patent Office (EPO), which are collected in the OECD, REGPAT Database, January 2014. REGPAT also exclusively attributes patent documents from China to provinces, but the database information is detailed enough to rearrange data at the prefectural level based on applicants' addresses (Callaert et al. 2011). In this regard, the dataset is new to the literature.

Regressions implement an OLS estimation of pooled cross-sectional data, preventing complexities due to serial autocorrelation and individual fixed effects in panel estimation. The analysis rests upon two analogous regression sets. The first consists of usual tests of convergence serving as benchmarks for discussion, and the second addresses group variability. Differences between convergence paces are expected to disappear, at least partially, by adding determinants to the estimation model.

4. Results and discussion

The results from conventional tests of growth convergence (Table 2) provide three basic hints. First, there is no absolute convergence across Chinese prefectures during the observed period (2.1), motivating the authors to then look into growth drivers as proxies for steady-state income levels. Second, all variables exhibit significant coefficients with the expected signs (2.2-2.5). Third, the estimated convergence rates are congruent with those usually presented in literature, although they are slightly higher. This evidence is however supposed to be consistent with fast economic growth.

[Table 2 near here]

Table 3 then reports the results from the second regression set. The coefficient associated with the initial income level y_{i0} can now vary across groups. The second and third subscript of y denote periods τ_t and regions ρ_i, respectively: 1996-2000 (1), 2001-2005 (2) and 2006-2010 (3); East (0), Midland (1), Northeast (2) and West (3). Accordingly, y_{i10} concerns Eastern prefectural cities between 1996 and 2000, while the other group-related coefficients are in differences from b_{10}.

[Table 3 near here]

When no proxy enters the model but the coefficient associated with the initial income level can vary, growth rates converge within groups (3.1). The estimated differences are indeed significant, confirming that convergence across groups is poor. Furthermore, additional variables still exhibit significant coefficients with the expected signs, and the model explanatory power earns 9 percentage points more with respect to the analogous regressions in Table 2 (3.2-3.5).

Finally, Table 4 reports the speed of convergence λ implied by regressions. The first row of values refers to the overall rates from Table 2, and the following rows refer to the local rates from Table 3. As mentioned, there is no overall possibility for latecomers to catch up with the richest cities without considering growth conditions (4.1 λ). Catch up, however, exists if restricted, for instance, to the Eastern prefectures between 1996 and 2010 (4.1 λ_{10}). In this group, a latecomer would need 18 years to catch up halfway with the frontier. In contrast, the same catch up would occur in 24 years in Midland between 2006 and 2010 (4.1 λ_{31}). In general, convergence rates also tend to decrease over time (4.1-4.5).

[Table 4 near here]

Introducing explanatory variables produces two more items of evidence. First, the speed of convergence increases. Fourteen years was indeed enough to halve the gap among Eastern prefectures between 1996 and 2000, considering the effect of IFDI (4.3 λ_{10}). The years needed to catch up further decreases to 11 if the model includes both IFDI and KS (4.5 λ_{10}). Then, they are actual sources of disparity within groups.

Second, significant differences between local convergence rates become less numerous. This also means that convergence across groups depends on the considered proxies. Human capital and KS, however, appear to be more effective than IFDI in capturing disparities, given that some differences are persistently significant when IFDI enters the model (4.3 λ_{20}, λ_{23}, λ_{31} and λ_{33}; 4.5 λ_{31} and λ_{33}). This suggests that the impact of these drivers on growth rates is probably uneven and the development path asymmetrical, reinforcing the hypothesis of structural disparities.

5. Conclusions

This paper shows that economic growth is structurally unbalanced in China. In doing this, it contributes to the literature with new data and methodological approach. More precisely, convergence rates across groups of prefectural cities vary with time and region and are conditional on usual endogenous growth drivers, as well as on IFDI and KS. EPO patents from China work to approximate structural disparities within and across groups, although they are highly selective in measuring the actual endowment of indigenous technological capabilities. This probably stresses the effectiveness of KS in capturing disparities and deserves more investigation. Baseline regression results are, however, satisfactorily congruent with those reported in the literature on growth empirics.

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Table 1. Description of variables and summary statistics (N=780).

	Description	μ	σ	*min*	*max*
y_{it}	GPD per capita at 2009 prices, log	9.571	0.869	6.611	12.815
y_{i0}	Initial level of GPD per capita at 2009 prices, log	9.134	0.778	6.654	12.658
s_i	Investment in fixed assets over GDP, 5-year average, log	–1.115	0.522	–2.722	0.111
d_i	Depreciation rate: population growth rate + 0.05, 5-year average, log	–2.892	0.056	–3.031	–2.559
h_i	Secondary school enrolment: number of students over population, 5-year average, log	–2.833	0.260	–4.472	–2.047
f_i	Inward Foreign Direct Investments over GDP, 5-year average, log	–4.399	1.286	–9.438	–0.610
k_i	Knowledge stock per million inhabitants, 5-year average, log	0.163	0.473	0	6.476

Table 2. Results from the first regression set (N=780).

	(2.1)	(2.2)	(2.3)	(2.4)	(2.5)
y_{i0}	0.005	-0.118^{***}	-0.139^{***}	-0.155^{***}	-0.174^{***}
s_{it}		0.304^{***}	0.312^{***}	0.313^{***}	0.319^{***}
d_{it}		-1.106^{***}	-1.132^{***}	-1.119^{***}	-1.144^{***}
h_{it}		0.405^{***}	0.396^{***}	0.400^{***}	0.391^{***}
f_{it}			0.028^{**}		0.026^{**}
k_{it}				0.094^{**}	0.091^{**}
R^2	0.000	0.240	0.247	0.249	0.255

OLS estimator; robust standard errors
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Results from the second regression set (N=780).

	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)
y_{i10}	–0.142***	–0.161***	–0.182***	–0.205***	–0.222***
$y_{i11}–y_{i10}$	–0.036***	–0.034***	–0.032***	–0.036***	–0.033***
$y_{i12}–y_{i10}$	–0.010*	–0.011*	–0.008	–0.012**	–0.009
$y_{i13}–y_{i10}$	–0.052***	–0.044***	–0.040***	–0.046***	–0.042***
$y_{i20}–y_{i10}$	0.025***	0.009	0.011*	0.008	0.010*
$y_{i21}–y_{i10}$	0.009	–0.007	–0.003	–0.007	–0.004
$y_{i22}–y_{i10}$	0.011**	–0.001	0.004	–0.001	0.004
$y_{i23}–y_{i10}$	0.022***	0.006	0.011*	0.004	0.008
$y_{i30}–y_{i10}$	0.023***	0.007	0.011*	0.003	0.007
$y_{i31}–y_{i10}$	0.029***	0.011	0.015**	0.011	0.014*
$y_{i32}–y_{i10}$	0.034***	0.017***	0.022***	0.018***	0.022***
$y_{i33}–y_{i10}$	0.028***	0.009	0.017**	0.009	0.016**
s_{it}		0.163***	0.151***	0.173***	0.163***
d_{it}		–0.854***	–0.878***	–0.860***	–0.880***
h_{it}		0.268**	0.268**	0.261**	0.260**
f_{it}			0.025**		0.022*
k_{it}				0.122***	0.118***
R^2	0.284	0.332	0.336	0.345	0.348

OLS estimator; robust standard errors
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Implied speed of converge λ.

	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)
λ	–0.001	0.031^{***}	0.037^{***}	0.042^{***}	0.047^{***}
λ_{10}	0.038^{***}	0.043^{***}	0.050^{***}	0.057^{***}	0.062^{***}
λ_{11}	0.048^{***}	0.054^{***}	0.060^{***}	0.068^{***}	0.073^{***}
λ_{12}	0.041^{*}	0.047^{*}	0.052	0.061^{*}	0.065
λ_{13}	0.053^{***}	0.057^{***}	0.062^{***}	0.072^{***}	0.076^{***}
λ_{20}	0.031^{***}	0.041	0.046^{*}	0.054	0.059
λ_{21}	0.035^{*}	0.045	0.051	0.059	0.064
λ_{22}	0.035^{**}	0.044	0.049	0.057	0.061
λ_{23}	0.031^{***}	0.042	0.046^{*}	0.056	0.060
λ_{30}	0.031^{***}	0.041	0.046^{*}	0.056	0.060
λ_{31}	0.029^{***}	0.040	0.045^{*}	0.054	0.058^{*}
λ_{32}	0.028^{***}	0.038^{***}	0.043^{***}	0.051^{***}	0.055^{***}
λ_{33}	0.030^{***}	0.041	0.045^{**}	0.054	0.057^{**}

λ and λ_{10}: * refers to the significance level of the estimated coefficients

$\lambda_{\tau\rho}$: * refers to the significance level of differences from λ_{10}

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$