Heterogeneous convergence

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HIGHLIGHTS

- Using US county-level data with 1921 cross-sectional observations.
- Estimate conditional convergence rates for 22 US states separately.
- Average convergence rate is 9.2%.
- Range includes estimates of 3.3% (New York); 19.9% (California).
- Estimated convergence rates essentially uncorrelated with income levels.

ARTICLE INFO

Article history:
Received 12 December 2011
Received in revised form 9 April 2013
Accepted 10 April 2013
Available online 26 April 2013

JEL classification:
O40
O11
O18
O51
R11
H50
H70

Keywords:
Economic growth
Conditional convergence
Heterogeneity
US county level data

ABSTRACT

We use US county-level data to estimate convergence rates for 22 individual states. We find significant heterogeneity. E.g., the California estimate is 19.9% and the New York estimate is 3.3%. Convergence rates are essentially uncorrelated with income levels.

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We are grateful to the referee for constructive comments that helped us improve the manuscript. We thank Steven Durlauf, Jordan Rappaport and Jerry Thursby for helpful comments and suggestions and Paul Evans for answering our questions. We are grateful to Jordan Rappaport for kindly sharing with us data and computer codes. Matthew Higgins acknowledges financial assistance from a National Science Foundation IGERT Fellowship and The Imlay Professorship. Daniel Levy gratefully acknowledges financial support from Adar Foundation of the Economics Department at Bar-Ilan University. All errors are our own.

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http://dx.doi.org/10.1016/j.econlet.2013.04.017
1. Introduction

Empirical conditional convergence studies implicitly assume that all economies follow identical growth processes and that, therefore, it is meaningful to estimate a single rate of convergence. However, Evans (1998) argues that this is implausible for most data sets because countries (p. 296) “…have different technologies, preferences, institutions, market structures, etc.”.1

We use county-level data from 22 individual states, comprising a total of 1,921 US counties to study heterogeneity in convergence rates. The data include per capita income growth and 29 other conditioning variables. Conditional on the latter, we report separate convergence rate estimates for each of these 22 states.

Existing studies of heterogeneity in growth represent a range of ingenious econometric techniques designed to cope with a limited number of observations typically available for growth studies.2 Given the richness of our data, we are able to explore heterogeneity in convergence rates amongst the US states by incorporating a large number of demographic and socio-economic variables as controls.

Our data offer several other advantages. A single institution collects it, ensuring uniform variable definitions. There is no exchange rate variation between the counties and the price variation across counties is smaller than across countries, reducing the potential errors-in-variables bias (Bliss, 1999).3 Counties within a state form a sample with geographical homogeneity and a shared state government. To a great extent the states are ready-made “clubs” within which we would expect convergence. The large data set allows us to study inter-state heterogeneity, while the intra-state homogeneity increases the accuracy likelihood of the specification we employ.

There are considerable per capita income differences across US states. While Higgins et al. (2006) find that US county-level data is well-described by conditional convergence, Young et al. (2008), using the same data, find that the actual dispersion of income levels is not decreasing. One possible explanation for this is that many individual states are not well-described by conditional convergence. Another possibility is that poorer economies have relatively low convergence rates. State-specific convergence rate estimates can help in assessing the plausibility of this explanation.

We find significant heterogeneity in the state-level convergence rates. Across the 22 states, we obtain a range of point estimates including 2.7% (Georgia) and 19.9% (California). The average convergence rate across these states is 9.2%. We also find that convergence rates and income levels are essentially uncorrelated, suggesting that poorer states are not at an inherent disadvantage in catching up to their richer counterparts.

The paper is organized as follows. Section 2 discusses the model and our estimation strategy. Section 3 describes the data. Section 4 reports the findings. Section 5 concludes.

2. Econometric model

As Barro and Sala-i-Martin (1992) show, the neoclassical growth model implies that $g_n = \alpha + \beta y_{nt} + \gamma' x_{nt} + \nu_n$, where $g_n$ is the average growth rate of per capita income for economy $n$ between years 0 and $T$, $\alpha$ is a function of the exogenous $n$ technical progress, and $\beta = (1 - e^{-\delta})/T$ with $B$ representing the responsiveness of the average growth rate to the gap between the steady state income and the initial value, $x_{nt}$ is a vector of control variables, $\gamma$ is a coefficients’ vector, and $\nu_n$ is a zero mean, finite variance error term.

We adapt the basic growth model to panel data:

$$g_n = \alpha + \beta y_{nt} + \gamma' x_{nt} + \nu_n$$

(1)

where $t$ indexes $T = 5$ years intervals that will begin in our data, at 1970, 1975, 1980, 1985, 1990, 1995, 2000, and 2005, and $g_n$ is a period fixed effect. For example, the first observation for a county $n$, will consist of $g_{n, 1970} = (y_{n, 1975} - y_{n, 1970})/5, y_{n, 1970}$, and $y_{n, 1970}$. We estimate (1) using generalized method of moments (GMM) including period fixed effects. Based on the estimate, $\beta$, we calculate the convergence rate point estimate as $\epsilon = 1 - (1 + T \hat{\beta})^{-1}$. To calculate a 95% confidence interval we compute $\hat{\beta} \pm (1.96 \times s.e.)$, where $s.e.$ is the standard error of $\hat{\beta}$. If the low value of the confidence interval is less than $-T^{-1}$, the higher value is set equal to one. Note that in general, the resulting confidence intervals will be asymmetric around the point estimates (Evans, 1997b).

3. US county-level data

We begin with US county level data that include 3,057 county-level observations covering all 50 states from 1970 to 2010. However, statistically significant convergence rates estimates can only be computed for 22 states (constituted by 1921 counties). We use the log of real per capita personal income net of transfers. We also start with 29 conditioning variables that correspond approximately to the set used by Higgins et al. (2006, 2009, 2010) and Young et al. (2008).4 The panel has a time dimension of 8.

Our identification strategy is to use lagged control variables as instruments. We initially run an OLS, period fixed effects regression of growth on initial income and all of the other controls. From that regression we identify 7 controls that are statistically insignificant. Of those we choose 4 to use as excluded instruments that create over-identification in our GMM estimations. This decreases our time dimension to 7.

4 The conditioning variables are collected at the county level and include: land and water area per capita; percentage of 5–13, 14–17, 18–64, and 65+ year olds; percentage of blacks and Hispanics; percentage of population with education of 9–11 years, high school diploma, some college, and bachelor degree or more; percentage of population below the poverty line; percentage of the population employed by federal, state, and local governments; percentage of self-employed; percentage of population employed in agriculture-fishing-and-forestry, construction, services, finance-insurance-and-real-estate, manufacturing, mining, retail, transportation and public utilities, wholesale trade, college town and metro area indicators. The few differences in the control variable set used here versus (Higgins et al., 2006) are the result of moving from a cross section of growth from 1970 to 1998 to the updated panel used here, from 1970 to 2005. This required using BEA rather than Census data. The BEA, for example, collapses some industry categories into a single category and redefines others.

5 Caselli et al. (1996) suggest GMM estimation based on first differencing the growth equation. Bond et al. (2001) suggest estimating a system including the first-differenced equation. We focus on the un-differenced growth equation because our controls represent evolving characteristics of economies; most of the information is in the levels. The excluded instruments are the college town indicator, the land area per capita, and the population percentages employed in transportation and public utilities and in wholesale trade. Of the other three not-significant controls from the OLS regression, two were educational attainment variables. The other was federal government employment that Higgins et al. (2010) find to be a robust correlate of growth.

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1 Levy and Dezghakh (2003) provide international evidence on output fluctuation and shock persistence that may be considered an indirect evidence of such heterogeneity.

2 See, e.g., Durlauf and Johnson (1995), Lee et al. (1997), Rappaport (2000), Brock and Durlauf (2001), Durlauf et al. (2001), and Rodrik (2012). See also the “club convergence” literature. For example, Quah (1996, 1997), Deidogits (1999), and Canova (2004).

3 These virtues are also embodied in state-level data (Barro and Sala-i-Martin, 1991; Evans, 1997a). State-level data, however, sacrifices the large number of observations we have. All 22 states we study have counties numbering more than 50 (the number of US states), and few of them twice as many and even more.
Table 1
Asymptotic conditional convergence rates for 22 US states using GMM: point estimates with 95% confidence intervals.

<table>
<thead>
<tr>
<th>State</th>
<th>No. of counties</th>
<th>Convergence rate; confidence interval</th>
<th>J-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>3,057</td>
<td>0.0058 (0.0029, 0.0086)</td>
<td>3.8680</td>
</tr>
<tr>
<td>Alabama</td>
<td>67</td>
<td>0.0543 (0.0013, 0.1181)</td>
<td>0.0098</td>
</tr>
<tr>
<td>Arkansas</td>
<td>74</td>
<td>0.1523 (0.0800, 0.2501)</td>
<td>0.0192</td>
</tr>
<tr>
<td>California</td>
<td>58</td>
<td>0.1989 (0.0984, 0.3648)</td>
<td>2.9370</td>
</tr>
<tr>
<td>Colorado</td>
<td>63</td>
<td>0.1915 (0.0822, 0.3829)</td>
<td>0.2804</td>
</tr>
<tr>
<td>Georgia</td>
<td>159</td>
<td>0.0269 (0.0032, 0.0525)</td>
<td>0.5088</td>
</tr>
<tr>
<td>Illinois</td>
<td>102</td>
<td>0.0565 (0.0319, 0.0832)</td>
<td>11.8745</td>
</tr>
<tr>
<td>Indiana</td>
<td>92</td>
<td>0.0674 (0.0336, 0.1052)</td>
<td>0.0699</td>
</tr>
<tr>
<td>Iowa</td>
<td>99</td>
<td>0.0399 (0.0063, 0.0749)</td>
<td>1.2048</td>
</tr>
<tr>
<td>Kansas</td>
<td>105</td>
<td>0.4697 (0.1405, 1.0000)</td>
<td>0.1072</td>
</tr>
<tr>
<td>Kentucky</td>
<td>120</td>
<td>0.0721 (0.0389, 0.1093)</td>
<td>0.0395</td>
</tr>
<tr>
<td>Louisiana</td>
<td>64</td>
<td>0.0566 (0.0011, 0.1240)</td>
<td>4.0071</td>
</tr>
<tr>
<td>Michigan</td>
<td>83</td>
<td>0.0376 (0.0158, 0.0609)</td>
<td>2.6696</td>
</tr>
<tr>
<td>Mississippi</td>
<td>82</td>
<td>0.0955 (0.0355, 0.1705)</td>
<td>3.9598</td>
</tr>
<tr>
<td>Missouri</td>
<td>114</td>
<td>0.0401 (0.0074, 0.0766)</td>
<td>1.0675</td>
</tr>
<tr>
<td>New York</td>
<td>62</td>
<td>0.0333 (0.0089, 0.0596)</td>
<td>0.6844</td>
</tr>
<tr>
<td>North Carolina</td>
<td>100</td>
<td>0.0600 (0.0335, 0.0889)</td>
<td>0.0605</td>
</tr>
<tr>
<td>Ohio</td>
<td>88</td>
<td>0.0558 (0.0250, 0.0899)</td>
<td>0.1431</td>
</tr>
<tr>
<td>Oklahoma</td>
<td>77</td>
<td>0.0753 (0.0312, 0.1267)</td>
<td>0.0984</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>67</td>
<td>0.0698 (0.0324, 0.1124)</td>
<td>1.3023</td>
</tr>
<tr>
<td>Tennessee</td>
<td>95</td>
<td>0.0858 (0.0322, 0.1510)</td>
<td>0.6911</td>
</tr>
<tr>
<td>Virginia</td>
<td>80</td>
<td>0.0474 (0.0150, 0.0833)</td>
<td>2.7240</td>
</tr>
<tr>
<td>Wisconsin</td>
<td>70</td>
<td>0.0395 (0.0151, 0.0660)</td>
<td>0.6419</td>
</tr>
<tr>
<td>Total</td>
<td>1,921</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Denote statistical significance at the 1% level.
** Denote statistical significance at the 5% level.
* Denote statistical significance at the 10% level.

Fig. 1. Point estimates of the within-state asymptotic convergence rates with 95% confidence intervals.

4. Convergence rate estimates

Table 1 reports the asymptotic conditional convergence rate estimates with 95% confidence intervals for 22 individual US states. Fig. 1 presents confidence intervals as vertical bars around the point estimates. The individual state estimates vary significantly, indicating cross-state heterogeneity. The average estimate for the 22-state sample is 9.2% and for 4 states the point estimate exceeds 10%. Table 1 also reports J-statistics. At better than the 10% level the over-identifying restrictions are rejected only 3 times; only 2 times at better than the 5% level.

Thus, there is considerable heterogeneity in the estimated convergence rates. The full picture that one gets from Table 1 and Fig. 1 is of a group of economies with high (typically above 5%) but often quite different rates of convergence. This heterogeneity should not be surprising. The convergence rate in the neoclassical growth model is a function of the technology and population growth rates, the depreciation rate, and the technology and preference parameters. Therefore, differences in the particular industries that predominate in an economy, cultural characteristics, and institutions may translate into different convergence rates.

A simple OLS regression of the state convergence rate point estimates on average per capita income levels yields a partial correlation of 0.1677 and it not statistically significant. This suggests that poorer economies are not in general facing relatively poor convergence potentials.

5. Conclusions

We use 1,921 US county-level observations to explore the variation in income convergence across the US states. Across 22 individual states, the estimated convergence rates average 9.2%. For 15 states the point estimate convergence rate is above 5%. We find substantial heterogeneity in individual state convergence rates.

The high convergence rates are encouraging in the sense that, given proper policies to induce and support balanced growth paths, laggard economies can close the gap relatively quickly. Convergence rates are, in principle, functions of deep technology and preference parameters. If these deep parameters differ enough across US states to create heterogeneous convergence, then one suspects that both the parameter and convergence rate differences might be meaningfully greater across countries.

References


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6 Kansas has an implausibly high estimate of about 47% and the confidence interval extends the graph to unity.