Economic Inquiry

# DISCONTINUITY OF OUTPUT CONVERGENCE WITHIN THE UNITED STATES: WHY HAS THE COURSE CHANGED?

CHI-YOUNG CHOI and XIAOJUN WANG*

*Has the progress of output convergence changed within the United States? This article examines the output convergence among U.S. states for the last five decades by making several improvements over the extant literature. By applying a battery of convergence tests designed to capture nonlinear transitional dynamics to* real *output per worker data (i.e., nominal values deflated by state-level price), we find that output convergence has not been a feature of the continental United States since the 1970s. Instead, output convergence has proceeded among four subgroups within which constituent states have certain characteristics in common. Our regression analysis suggests that state-level characteristics related to technology and human capital play a crucial role in accounting for the formation and composition of convergence clubs, in agreement with the recent theoretical models of growth and development (e.g., Aghion et al. 2009; Gennaioli et al. 2013b). The level of technology, proxied by patents, turns out to be a consistently significant determinant even after controlling for endogeneity, suggesting that frictions in the diffusion of technology and human capital may have led to clustering of states with different levels of productivity. Our results therefore cast doubt on the common view that diffusion of knowledge and technology across state borders is frictionless.* (*JEL* O47, O51)

## I. INTRODUCTION

The standard neoclassical growth theory predicts that economies with similar technologies and preferences should ultimately converge toward the same standard of living. This convergence prediction is particularly relevant for subnational economies, such as the states in the United States, which share nearly identical institutional environments with a high mobility of technology and production factors. In fact, ever since the seminal work by Barro (1991) on output convergence among the U.S. states, a large number of researchers have documented that the standard of living of residents of the U.S. states has converged over time (e.g., Barro and Sala-i-Martin 2004; Mitchener and McLean 1999, 2003). This prevailing view in the literature, however, has been called into question by more recent studies which claim that the process

*The paper has been greatly improved by the constructive comments and suggestions of Wesley Wilson (editor) and two anonymous referees. The authors are also grateful to Daniel Allen and Arsalan Nadeem for research assistance and to Marco Del Negro and Robert Tamura for kindly sharing their data. We thank Andrew Ching, Yongwan Chun, Paul Evans, Sumner La Croix, Roger Meiners, Donggyu Sul, Mike Ward, Steve Yamarik, and Mahmut Yasar for helpful comments and suggestions. Part of the research was conducted when Choi was visiting the Institute of Economics at Academia Sinica, Taiwan. Choi gratefully acknowledges the Institute's support and hospitality during his visit. Any remaining errors are the authors' own.

*Choi:* Associate Professor, Department of Economics, University of Texas at Arlington, Arlington, TX 76019. Phone 1-817-272-3860, Fax 1-817-272-3145, E-mail cychoi@uta.edu

*Wang:* Associate Professor, Department of Economics, University of Hawaii at Manoa, Honolulu, HI 96822 and CEFMS, Hunan University, Changsha, Hunan, China. Phone 1-808-956-7721, Fax 1-808-956-4347, E-mail xiaojun@hawaii.edu

**ABBREVIATIONS**

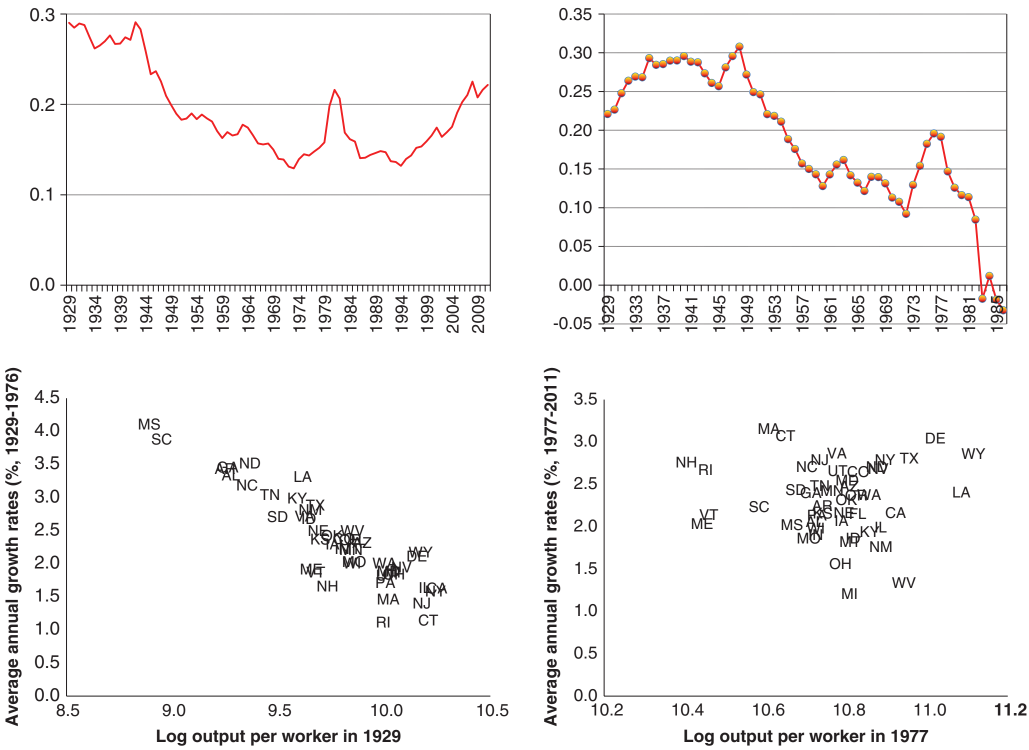
BEA: Bureau of Economic Analysis
CPI: Consumer Price Index
CV: Coefficient of Variation
DEA: Data Envelopment Analysis
GMM: Generalized Method of Moments
GSP: Gross State Product
PS: Phillips and Sul
RMA: Recursive Mean Adjustment
RSC: Residual Squares Criterion
RTP: Relative Transition Path
SPI: State Personal Income
WTF: World Technology Frontier



Economic Inquiry
(ISSN 0095-2583)
Vol. 53, No. 1, January 2015, 49–71

doi:10.1111/ecin.12129
Online Early publication August 4, 2014

**FIGURE 1**
Conventional Measures of Output Convergence for the Log Real Output per Worker




of output convergence in the United States stalled in the 1970s (e.g., Bauer, Schweitzer, and Shane 2006; Ganong and Shoag 2012).[1]

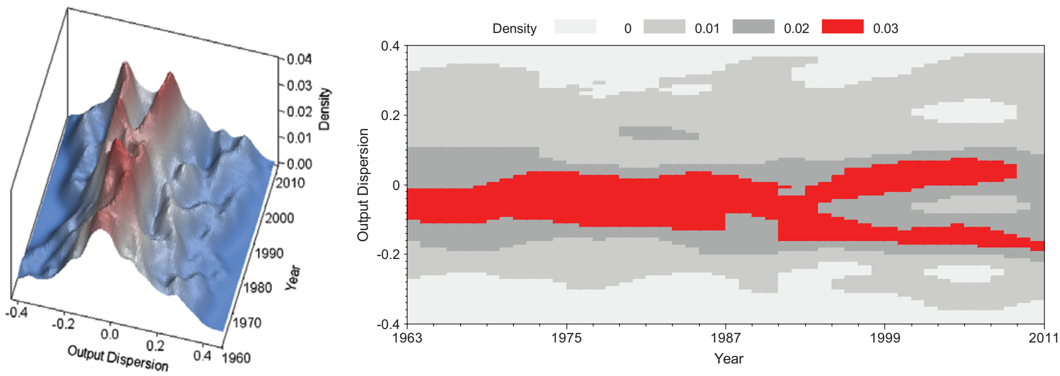
Inspired by this, we plot in Figure 1 two conventional measures of output convergence for the log output per worker of the 48 continental U.S. states since 1929.[2] Our inspection of the top-left panel of Figure 1 suggests that there has been a convergence in output among the U.S. states over much of the twentieth century as widely documented in the literature. The output dispersion across states, measured by the coefficient of variation (CV), continuously declined until the mid-1970s. Output convergence, however, does not appear to be a feature throughout the rest of the period because the dispersion has hitherto increased gradually. A similar picture is painted in the top-right panel of Figure 1 which plots the estimated speed of β-convergence in the spirit of Barro and Sala-i-Martin (1992).[3] The rolling 25-year estimate of β drops drastically from positive values to near zero in the late-1970s, indicating that cross-state output evolution switched from convergence to divergence. This can be viewed from a slightly different angle in the bottom panels of Figure 1, which present two scatterplots of the logged values of initial output level (horizontal axis) against the average annual growth rates (vertical axis) for each state before and after 1977. A clear inverse association is noted in the bottom-left panel

1. Bauer, Schweitzer, and Shane (2006) document that the dispersion of state per capita incomes has risen from 1976, in large part stemming from the departure of some relatively high-income states relative to the national average. Ganong and Shoag (2012) claim that tight regulations on land use weakened convergence in per capita income among U.S. states after 1980.

2. The data used here, generously supplied by Robert Tamura for 1929–2000, are extended by us to 2011. We are grateful to Robert Tamura for sharing the data with us.

3. β-convergence occurs when originally poor economies grow faster than richer ones so that all economies eventually converge in terms of real per capita output. A positive value of β in Equation (1) below indicates evidence of β-convergence. σ-convergence occurs when the dispersion of real per capita output across a group of economies declines over time.

**FIGURE 2**
Evolution of the Log Real Output per Worker Distribution (1963–2011)




between the average growth rate between 1929 and 1976 and the log output per worker in 1929, indicating strong evidence of β-convergence. As shown in the bottom-right panel, however, there is no evidence of convergence after 1977 when the negative relationship disappeared completely, in line with our earlier observation. As a further piece of evidence, Figure 2 displays dynamics of cross-state output dispersion densities along the lines of Quah (1996). The left panel of Figure 2 tracks the evolution of the density distributions since 1963. Notice that the distribution appears to have undergone a notable shift from nearly unimodality to multimodality around the 1970s, thereafter the distribution collates into several clubs or subgroups. This change in output distribution is also reflected in its contour pattern exhibited in the right panel of Figure 2, where the single distribution mass has clearly split into a multitude during the latter sample period. Combined together, our visual inspection of Figures 1 and 2 convincingly suggests that the process of output convergence in the United States stopped in the 1970s and hence output convergence may no longer be a viable hypothesis for the U.S. states in the ensuing period.

It is natural to wonder, then, what happened to the development of output convergence in the United States after the 1970s and what factors are behind it. The primary objective of this study is to shed light on these questions by making several improvements over the previous literature. To begin, this study focuses on the past five decades when the output convergence process stalled in the United States, in lieu of the century-long period that has been popularly studied in the previous literature. The reason for this is twofold. First, while a near consensus has been formed in the literature on the convergence experience in the United States prior to the 1970s, there has been relatively little formal effort to explore the period after that. In light of our visual impression of the discontinuity of output convergence among U.S. states, it would be illuminating to analyze how the cross-state output differences have proceeded in the following period. Second, focusing on a more recent time period permits us to utilize an arguably more appropriate measure of state-level output. While it has been customary in the literature to construct state-level real output data by deflating state personal income (SPI) data using a common national price index, deflating in this way, as emphasized by Barro and Sala-i-Martin (1992) and Mitchener and McLean (1999), leads to mismeasurement of real per capita state income when price dynamics differ considerably across states.[4] Since nominal output series comprise both real output and price, it is hard to tell whether empirical evidence on convergence in nominal output is driven by

4. Choi (2004) sought to deal with this issue by using metropolitan area CPIs as a proxy, but the use of metropolitan area CPIs is of limited merit for answering the question at hand, not just because they are unavailable for all states, but because they are not good representatives of state-level prices, especially for those states with a low urbanization rate. Another important attempt to account for state price differences has been made by Turner et al. (2006) who constructed real state output per worker, from 1840 to 2000. They, however, utilized regional price levels for eight census regions at 20-year intervals from 1840 to 1960 and used Berry and Fording (2000) annual state cost of living index from 1960 to 1995.

convergence in real output or by convergence in price level. With a few notable exceptions (e.g., Mitchener and McLean, 1999; Turner et al. 2006), the extant literature has largely remained silent on this critical issue mainly due to the paucity of proper state-level price data for a sufficiently long period. In the current study, we tackle this issue by using gross state product (GSP) data in which both nominal and real output series are available. Since the real GSP data are currently available only after 1977, we extend the series back to 1963 using the state consumer price index (CPI) data borrowed from Berry and Fording (2000) as in Turner et al. (2006). Consequently, our sample period for *real* output per worker spans for almost five decades from 1963 to 2011.

Another distinctive feature of our study rests on the methodological approach. Although the pattern of output convergence remains an unsettled issue, it is now widely documented that nonlinear specifications provide a superior characterization of the dynamics of output convergence processes (e.g., Durlauf et al. 2006; Henderson et al. 2012; Phillips and Sul 2009). Much of the previous studies on output convergence among U.S. states have resorted to conventional and popular approaches based on linear models, such as the cross-section methods of β- and σ- convergences or the time-series method of stochastic convergence (e.g., Carlino and Mills 1993; Evans and Karras 1996; Heckelman 2013; Young et al. 2008), but they may be of reduced merit for capturing the transitional dynamics of state-level output observed in the 1970s. In fact, our analysis based on nonparametric techniques uncovers the nonlinear and time-varying behavior of the U.S. output process. One of the main challenges in this regard is to select a specific form of nonlinearity in the absence of any guidance from theoretical models. Durlauf et al. (2006) stressed the usefulness of the econometric tools proposed by Phillips and Sul (2007, 2009; hereafter referred to as PS) in capturing the transitional dynamics of output processes toward steady states. Based on a nonlinear time-varying dynamic factor model, the PS technique enables us to test the convergence hypothesis across a wide spectrum of nonlinear dynamics by allowing for heterogeneity in parameters over time as well as across states.

By applying the PS methods to the real output per worker of the 48 continental U.S. states, we find that states had not fully converged over the last five decades, as evidenced by the significant difference in output that has persisted across states. A clustering algorithm reveals the presence of four distinctive subgroups of convergence, or convergence clubs, each of which comprises states with similar dynamic patterns of output. To identify the potential factors that are conducive to the formation and specific compositions of convergence clubs, we carry out a further regression analysis and find a few key state-level characteristics that are shared in common among states in the same clubs. Among them, variables related to knowledge accumulation, such as patents and educational attainment, turn out to play an important role in determining states' club membership. States with higher levels of these variables are likely to fall into the club of a higher productivity, consistent with the finding of Glaeser and Saiz (2004) that knowledge stock is meaningfully correlated with the living standard of states.

Our empirical findings are compatible with the prediction of recently developed growth theories. In a multistate endogenous growth model, for instance, Aghion et al. (2009) show that cross-state differences in economic growth within the United States are mainly determined by states' proximities to the technological frontier, which are often proxied by patents. Gennaioli et al. (2013a and 2013b) also present a modified version of the neoclassical growth model in which they attribute the highly persistent disparities in regional incomes and the consequent multiple growth regimes to a wide cross-regional variation in educational attainment resulting from barriers to factor mobility. The authors raise a serious question on the empirical validity of the common view that diffusion of knowledge and technology across state borders is frictionless. In fact, Allen and Arkolakis (forthcoming) recently claim that a substantial fraction of the spatial variation in incomes across the United States can be explained by geographic location alone. Provided that technology and production factors do not move freely due to spatial frictions, the distribution of technology and knowledge would give rise to a considerable variation in the regional standard of living. This point is vindicated by our further analysis based on a nonparametric deterministic frontier approach which reveals significant cross-state differences in the level of technology. While states belonging to the high-income club are either on the frontier or very close to it, states in the low-income club are far below the frontier. The discontinuity of the output convergence process is conjectured to have been driven to a great extent by these factors as they played larger roles after the 1980s due to the technology- and human capital-intensive feature of the information era (e.g., Oliner and Sichel 2000).

The remainder of the paper is organized as follows. Section II begins with a brief discussion of the data and its preliminary analysis. Section III is devoted to an explanation of the econometric analysis focusing on the methodology developed by PS. The results of the convergence test and the clustering algorithm are also discussed in this section, together with theoretical implications of our empirical findings. Section IV conducts regression analysis based on discrete dependent models to identify the state-level characteristics responsible for the formation and composition of convergence clubs. In this section, we also check the robustness of our empirical findings against the well-known issue of endogeneity. Section V concludes the paper.

## II. DATA AND PRELIMINARY ANALYSIS

### A. *The Data*

To compare the economic performance of different states, we use *annual* GSP per worker (henceforth, output per worker), published by the Bureau of Economic Analysis (BEA: http://www.bea.gov/regional), for the 48 continental U.S. states over the period 1963–2011. As a comprehensive measure of state-level output, GSP is defined as the sum of output produced within a given state by all factors used in the state regardless of their owners' residence, and hence is different from another popular measure of state-level output, SPI, which is based on income generated by state residents.[5]

An attractive feature of the GSP data, relative to the alternative measures of state-level output including SPI, must be the availability of state price deflator data, which allows us to distinguish *real* output from nominal output. As is widely recognized, this distinction is intuitively important because the two measures of output are known to have very different time-series properties especially when price dynamics differ greatly across states. Unfortunately, the GSP deflator data are available for a relatively short time period (i.e., only after 1977). To deal with this issue, we utilize the state cost of living index data constructed by Berry and Fording (2000) and provided on William Berry's web page (http://pubadm.fsu.edu/archives) to deflate nominal GSP series prior to 1977. We extend the sample back as far as possible so that we can study the long-run evolution of state real output per worker. Specifically, all nominal GSP values are converted into real 2000 dollars after extending the GSP deflator index back to 1963.[6] As a result, our sample spans from 1963 to 2011, resulting in 49 annual observations of real GSP per worker for each of the 48 continental U.S. states.

Another notable feature of our data is that we focus on output *per worker* or labor productivity, instead of output per capita, as our measure of states' standard of living. This is because we view it more compatible with theoretical models, such as growth accounting. The difference between the two measures largely reflects the labor force participation rate difference across states. While output per capita can provide a general picture of a state's prosperity, output per worker can be viewed as an approximate indicator of a state's productivity. As noted by Bauer and Lee (2006), productivity measures are important to economists and policymakers partly because they provide a measure of a state's competitive position over time at the state level, and more because their growth is closely related to gains in the standard of living.[7]

5. According to the BEA ("GDP by State Estimation Methodology," p. 1), GSP consists of three major components: (a) compensation of employees (wages and salaries and their supplements); (b) taxes on production and imports; and (c) gross operating surplus (including noncorporate income). Among them, compensation of employees is shared by SPI. Because the two measures differ in the subcomponents, they are expected to take different profiles of convergence. For example, the wage and salary earned by residents in New Jersey who work in New York City will be part of SPI in NJ but GSP in NY. If workplaces are located in richer states than residences, use of SPI as the measure of state output may exaggerate output convergence because of the "distribution effect" through employee transfers. Though not reported here for brevity, we find a faster rate of convergence using SPI data than using GSP data. The reader is referred to Kalemi-Ozcan et al. (2010, p. 783) for a further discussion on the difference between GSP and SPI.

6. The real GSP data are not without criticism. Since real GSP is computed by deflating nominal GSP using the national GDP deflator after adjusting for states' industry composition, it may not properly reflect cross-state price variations. Nevertheless, we stick to this measure of output because there is no other consistent measurement of prices at the state level. We also considered Del Negro's (2002) state CPI data which are constructed using American Chamber of Commerce Association data on Cost of Living by metropolitan areas. But, the CPI data are available only for the period after 1969.

7. Though the number of hours worked is a preferred measure of labor input in constructing state-level productivity, we compute output per worker for the private nonfarm business economy as our productivity measure because data on the number of working hours are unavailable at the state level.

In order to estimate the U.S. technology frontier in Section IV.D, we also utilize a dataset employed in Turner et al. (2006) for the state-level physical and human capital for the period 1963–2000.

### B. *Preliminary Analysis*

Table 1 presents the summary statistics for three variables of interest at the state level: nominal output per worker, real output per worker (using 2000 as the base year), and inflation rates. Two interesting results emerge from Table 1. First, a broad-based difference exists in the behavior between nominal and real output per worker, especially in terms of annual growth rates. Virginia (VA), for instance, has experienced a relatively high growth rate of nominal output per worker (5.2%), ranking 9th in the nation; however, this rapid growth was largely driven by a high inflation rate (4.4%) rather than by real output growth. When the nominal output was adjusted for state price level, the annual growth rate of real output per worker in VA was just 0.7%, ranking 27th in the nation. Second, a considerable variation is noted across states in all of the three variables. Cross-state dispersion is particularly noticeable in real output per worker, judging from the large magnitudes of SD and CV shown at the bottom of Table 1. In terms of CV, the dispersion of real output growth is almost seven times as large as that of nominal output growth. Since cross-sectional variation is conceptually related to σ-convergence that looks at dynamic evolution of the cross-state output dispersion, this implies that inference drawn from nominal output data is likely to overstate the true underlying output convergence.

A similar story is told from Figure 3 which displays the estimated speed of β-convergence for real and nominal output per worker. Convergence speed is estimated from the conventional cross-sectional growth regression model (e.g., Barro and Sala-i-Martin 1992),

$$(1)\qquad t^{-1}\log\left(y_{it}/y_{i0}\right)=\alpha-\left[\left(1-e^{-\beta t}\right)/t\right]\times\log\left(y_{i0}\right)+u_{it},$$

where $y_{i0}$ is the initial level of output per worker in state $i$, $t^{-1}\log(y_{it}/y_{i0})$ denotes the growth rate of output per worker between time 0 and $t$, and $t$ is the length of the sample. In this exposition, positive values of β estimate are interpreted as evidence of β-convergence, while negative values or zero indicate divergence or lack of convergence. To capture potential time-varying behavior of the convergence speed, we use a rolling regression approach with a rolling window of 25 years.

**FIGURE 3**
Rolling 25-Year Estimate of β for Real (Dashed Line) and Nominal (Solid Line) Output

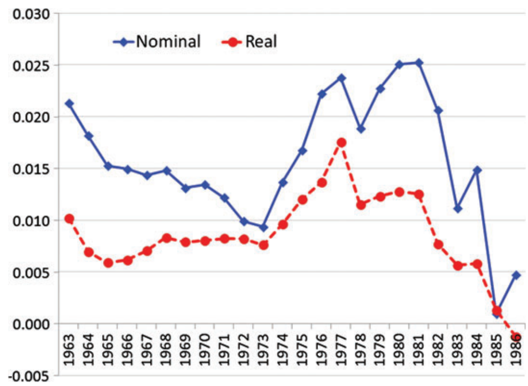



Figure 3 plots the corresponding rolling estimates of β: the solid line is for nominal output, while the dashed line is for real output. The numbers on the horizontal axis represent the beginning year of each 25-year window, so that 1973 captures the subsample period of 1973–1997, and so on. As can be seen from the plots, the β estimate for real output data is consistently smaller than that of nominal output data over the entire sample period. This implies that using nominal output may overstate the true speed of convergence by failing to take into account the impact of price changes, which facilitates the convergence process of nominal output.[8] Moreover, the β estimates for both nominal and real output drop near to zero in the late 1970s, indicative of the discontinuity of convergence process. This echoes what we have seen in the previous section regarding the halted convergence process. Taken together, the significant difference observed in the behavior between nominal and real output data stresses the importance of drawing inference from real output data.

8. The literature is replete with empirical evidence on more homogeneous dynamics of prices across states than real output. Henriksen et al. (2009), for instance, documented that the cross-country correlation of prices is substantially higher than that of (real) output. For a dissenting view, see Chen et al. (2008) who contended that the convergence of output took place earlier than that of prices across 11 countries.

**TABLE 1**
Descriptive Statistics of Labor Productivity for the 48 States (1963–2011)

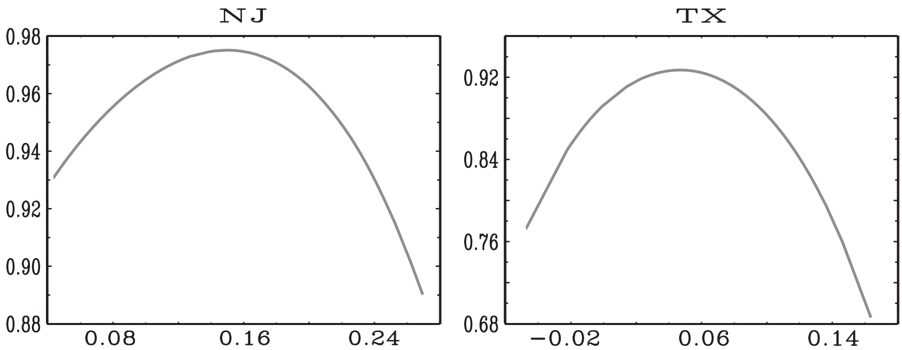
| | Nominal Output per Worker | | Real Output per Worker | | | |
|---|---|---|---|---|---|---|
| **State** | **Average** | **Growth** | **Average** | **Growth** | **Inflation Rate** | **Club** |
| AL | 33,634 [41] | 4.9 [24] | 44,766 [37] | 0.6 [34] | 4.3 [11] | 3 |
| AZ | 39,735 [17] | 4.8 [28] | 51,504 [21] | 0.9 [17] | 3.9 [41] | 2 |
| AR | 33,405 [42] | 4.9 [21] | 43,862 [41] | 0.8 [26] | 4.1 [19] | 3 |
| CA | 49,656 [4] | 5.1 [13] | 64,054 [5] | 1.1 [7] | 4.0 [33] | 1 |
| CO | 41,696 [14] | 5.2 [7] | 54,320 [14] | 1.1 [6] | 4.1 [27] | 2 |
| CT | 52,430 [2] | 5.4 [2] | 67,207 [2] | 1.3 [4] | 4.1 [25] | 1 |
| DE | 53,101 [1] | 5.4 [1] | 72,212 [1] | 1.0 [10] | 4.4 [5] | 1 |
| FL | 38,538 [24] | 5.0 [19] | 52,219 [18] | 0.7 [31] | 4.3 [6] | 2 |
| GA | 39,058 [20] | 5.3 [5] | 50,634 [23] | 1.1 [8] | 4.2 [13] | 2 |
| ID | 33,953 [37] | 4.6 [40] | 43,243 [43] | 0.9 [13] | 3.6 [47] | 3 |
| IL | 45,218 [9] | 4.9 [23] | 58,741 [9] | 0.9 [14] | 4.0 [35] | 2 |
| IN | 38,175 [26] | 4.6 [41] | 49,956 [24] | 0.6 [32] | 3.9 [39] | 2 |
| IA | 35,828 [35] | 4.6 [39] | 45,610 [35] | 0.8 [22] | 3.8 [45] | 3 |
| KS | 35,852 [34] | 4.7 [34] | 47,958 [30] | 0.6 [33] | 4.0 [30] | 3 |
| KY | 36,536 [30] | 4.1 [47] | 49,493 [27] | 0.1 [46] | 4.1 [23] | 3 |
| LA | 46,001 [7] | 4.8 [29] | 64,156 [4] | −0.1 [48] | 4.9 [1] | 2 |
| ME | 33,073 [43] | 5.0 [20] | 45,083 [36] | 0.7 [30] | 4.2 [12] | 3 |
| MD | 39,788 [15] | 5.1 [14] | 53,703 [15] | 0.8 [24] | 4.3 [10] | 2 |
| MA | 45,309 [8] | 5.4 [3] | 57,592 [13] | 1.5 [3] | 3.9 [40] | 1 |
| MI | 41,784 [13] | 4.1 [48] | 58,291 [10] | 0.0 [47] | 4.0 [29] | 2 |
| MN | 39,530 [18] | 4.8 [27] | 51,661 [20] | 0.8 [21] | 4.0 [34] | 2 |
| MS | 31,671 [47] | 4.7 [36] | 42,074 [46] | 0.3 [44] | 4.4 [4] | 4 |
| MO | 36,909 [28] | 4.7 [37] | 49,726 [26] | 0.6 [37] | 4.1 [24] | 3 |
| MT | 31,727 [46] | 4.5 [44] | 42,640 [44] | 0.4 [43] | 4.1 [22] | 4 |
| NE | 33,776 [40] | 4.8 [31] | 43,462 [42] | 0.8 [19] | 3.9 [37] | 3 |
| NV | 42,822 [12] | 4.7 [38] | 59,578 [8] | 0.5 [40] | 4.2 [15] | 2 |
| NH | 38,973 [22] | 5.4 [4] | 47,734 [31] | 1.6 [1] | 3.7 [46] | 2 |
| NJ | 48,629 [5] | 5.0 [18] | 63,614 [6] | 0.9 [12] | 4.1 [26] | 1 |
| NM | 36,293 [31] | 4.3 [45] | 44,586 [38] | 0.5 [38] | 3.8 [43] | 3 |
| NY | 50,584 [3] | 5.1 [17] | 66,602 [3] | 1.0 [11] | 4.0 [28] | 1 |
| NC | 37,837 [27] | 5.1 [10] | 49,485 [28] | 0.8 [20] | 4.3 [8] | 2 |
| ND | 30,753 [48] | 4.8 [30] | 39,451 [48] | 0.8 [23] | 3.9 [36] | 4 |
| OH | 39,103 [19] | 4.5 [43] | 52,237 [17] | 0.4 [42] | 4.0 [31] | 3 |
| OK | 35,903 [33] | 4.8 [26] | 47,594 [33] | 0.4 [41] | 4.3 [7] | 3 |
| OR | 38,836 [23] | 5.1 [15] | 49,885 [25] | 1.5 [2] | 3.5 [48] | 2 |
| PA | 39,746 [16] | 4.9 [22] | 52,646 [16] | 0.7 [28] | 4.2 [16] | 2 |
| RI | 38,981 [21] | 5.3 [6] | 51,365 [22] | 1.1 [9] | 4.2 [17] | 2 |
| SC | 32,628 [44] | 5.2 [8] | 42,222 [45] | 0.9 [16] | 4.3 [9] | 2 |
| SD | 32,336 [45] | 5.1 [16] | 40,143 [47] | 1.2 [5] | 3.8 [42] | 2 |
| TN | 36,826 [29] | 5.1 [12] | 48,567 [29] | 0.9 [18] | 4.2 [14] | 2 |
| TX | 44,444 [10] | 5.1 [11] | 57,886 [12] | 0.7 [29] | 4.4 [3] | 2 |
| UT | 34,932 [36] | 4.8 [25] | 46,142 [34] | 0.8 [25] | 4.0 [32] | 3 |
| VT | 33,847 [38] | 4.7 [33] | 44,193 [40] | 0.9 [15] | 3.8 [44] | 3 |
| VA | 38,320 [25] | 5.2 [9] | 51,716 [19] | 0.7 [27] | 4.4 [2] | 2 |
| WA | 44,041 [11] | 4.7 [32] | 60,235 [7] | 0.6 [35] | 4.1 [20] | 2 |
| WV | 33,826 [39] | 4.3 [46] | 44,223 [39] | 0.2 [45] | 4.1 [21] | 4 |
| WI | 36,176 [32] | 4.5 [42] | 47,642 [32] | 0.6 [36] | 3.9 [38] | 3 |
| WY | 47,244 [6] | 4.7 [35] | 58,007 [11] | 0.5 [39] | 4.2 [18] | 2 |
| Average | 39,155 | 4.9 | 51,457 | 0.8 | 4.1 | |
| SD | 5726 | 0.33 | 7786 | 0.36 | 0.23 | |
| CV | 0.15 | 0.07 | 0.15 | 0.47 | 0.06 | |

*Note*: Real output data are constructed using 2000 as the base year. Entries inside the square brackets denote the ranking among 48 states.

Another crucial data-related issue in the convergence literature is uncertainty regarding model specifications. While previous research has predominantly focused on linear models for characterizing convergence process, there is no solid justification for linearity especially in the absence of any theoretical guidance on the functional form. In view of the extensive empirical evidence of nonlinearities in output convergence (e.g., Durlauf et al. 2006; Henderson et al. 2012), it would be instructive to identify the functional form of the underlying convergence processes prior to drawing inference from the data. To this end, we follow

**FIGURE 4**

Nonparametric Estimation of Local Speed of Convergence: Departure from the Cross-Sectional Average (on the Horizontal Axis) and Convergence Rate (on the Vertical Axis)




Shintani (2006) and adopt a nonparametric approach that allows for flexibility in identifying functional forms of underlying series. The basic idea of this nonparametric approach is to estimate an unknown nonlinear autoregressive model of $y^d_{i,t} = m(y^d_{i,t-1}) + \epsilon_{i,t}$, where $y^d_{i,t} = y_{i,t} - (1/N)\sum_{i=1}^{N} y_{i,t}$ denotes the $i$th-state's output deviation from the cross-sectional average. The conditional mean function $m(y_{t-1})$ captures the average local speed of convergence and the underlying functional form of $m(\cdot)$ is identified without imposing any specific parametric restriction on the structure. The first derivatives of $m(y_{t-1})$ are then estimated using *local quadratic regression* with the Gaussian kernel.[9] The estimated local speed of adjustment would be constant if the true underlying process is linear, while it changes with the level of real output per worker if the underlying process is not linear. Figure 4 illustrates the estimated local speed of adjustment for real output per worker for a couple of selected states, NJ and TX. Since none of them looks flat, the adjustment process of real output per worker is likely to be *nonlinear*.[10] The nonmonotonic shapes, however, indicate that no single specific nonlinear model can capture all of the various dynamics. For this reason, most tools popularly adopted in the convergence literature are of limited appeal due to their linearity assumption. As emphasized by PS (2009), conventional cross-sectional tools for convergence testing, such as β- and σ-convergence, are susceptible to inconsistency and bias problems in the presence of nonlinear and heterogeneous transitions in growth patterns. Inference on stochastic convergence also becomes fragile since standard techniques based on unit-root and cointegration tests are known to suffer from a poor power problem in distinguishing a nonlinear but stationary process from a nonstationary process (e.g., Choi and Moh 2007).

## III. TESTING FOR CONVERGENCE AND THEORETICAL UNDERPINNINGS

Our discussion in the previous section highlights the importance of accounting for underlying nonlinear dynamics in the study of output convergence. Here we employ the technique developed by PS (2007) which is known to be suitable for accommodating a wide spectrum of nonlinear models, including transitional dynamics (e.g., Durlauf et al. 2006). Based on a nonlinear time-varying dynamic factor model, the intuition behind the PS technique is to test for long-run convergence by examining whether the cross-sectional dispersion of real output decreases over time. The PS method consists of two parts. The first part concerns testing for convergence using the so-called log-$t$ test and the second part is a clustering algorithm that applies the log-$t$ test to subsets of data when the null hypothesis of convergence is rejected for the full

9. Following Shintani (2006), we choose the smoothing parameter for the nonparametric estimator by minimizing the residual squares criterion (RSC) given in Fan and Gijbels (1996). The reader is referred to Shintani's original work for further details.

10. We find similar results for all other states. A complete version of Figure 4 is available at: http://wweb.uta.edu/faculty/cychoi/research.htm.

sample. The reader is referred to their original work for a more detailed description of the PS method.

### A. The Log-t Convergence Test

Let $y_{it}$ denote the real output per worker of state $i$ at time $t$ which is assumed to follow a nonlinear factor model

$$\log y_{it} = b_{it}\mu_t, \tag{2}$$

where $\mu_t$ represents a common steady-state growth path and $b_{it}$ denotes a time-varying idiosyncratic element measuring the heterogeneous transition path of state $i$ to $\mu_t$. Notice that this model embraces the time-series and cross-sectional heterogeneity of technological progress that is endogenously determined. The transition coefficient $b_{it}$ is further modeled as

(3)

$$h_{it} = \log y_{it} \Big/ \left( N^{-1} \sum_{i=1}^{N} \log y_{it} \right) = b_{it} \Big/ \left( N^{-1} \sum_{i=1}^{N} b_{it} \right),$$

where $h_{it}$ is called the relative transition path (RTP) measuring economy $i$'s relative departure from $\mu_t$. Under the null hypothesis of growth convergence, the following log-$t$ regression model can be formulated:

$$\log\left(H_1/H_t\right) - 2\log(\log t) = \alpha + \gamma \log t + u_t, \quad \text{for } t = T_0, \ldots, T,$$

where $H_t$ is the quadratic distance measure of $H_t = N^{-1}\sum_{i=1}^{N}\left(h_{it}-1\right)^2$ and $T_0$ and $T$, respectively, denote the initial and last observations in the regression. A one-sided $t$-test is then constructed such that output converges over time if $\gamma \geq 0$ and diverges if $\gamma$ is negative. If $\gamma \geq 2$, there exists an absolute convergence of output, whereas $2 > \gamma \geq 0$ implies a conditional convergence of output.

Before applying the log-$t$ convergence test to state output data, it would be informative to track the behavior of the relative transition curves in Equation (3) that captures the transitional and convergence behavior of real output over time relative to the common factor ($\mu_t$).[11] Relative convergence takes place if those transition curves converge toward unity over time. The top panel of Figure 5 shows the relative transition curves for the entire 48 states. The transitional pattern looks quite heterogeneous across states due to cross-sectional and time-series heterogeneity in state output per worker, and it shows no pattern of convergence toward unity over time, indicating a lack of convergence in the full sample.

Turning to the results of the log-$t$ test, the first row of Table 2 shows that the log-$t$ test strongly rejects the null hypothesis of convergence for the full sample, confirming the visual evidence shown in the top panel of Figure 5. Since the point estimate of $\gamma$ is significantly negative, $\hat{\gamma} = -0.545$, the null hypothesis of convergence can be rejected even at the 1% level. This result runs counter to the findings of earlier studies, including that of PS, which are typically based on nominal output deflated by a common national price for a longer sample period.[12] But, it is consistent with the recent evidence on the end of output convergence in the United States. This can be viewed as saying that the impact of the conventional driving forces of output convergence has diminished since the 1970s.

### B. Clustering Algorithm and Convergence Clubs

The lack of overall convergence motivates us to probe the possibility of convergence in its subgroups, or convergence clubs. Given that the log-$t$ convergence test would reject the null of convergence in the presence of as few as only one divergent series, the rejection could be compatible with many different scenarios, including convergence among some subgroups of states. To check whether convergence takes place in any subsets of states, we exploit the *clustering mechanism procedure* proposed by PS, which involves a stepwise and recursive application of log-$t$ regression tests to subsamples. As described in detail in their original work (e.g., Phillips and Sul 2009, p. 1170), the basic idea of the clustering mechanism is to split the full sample, which was rejected by the log-$t$ test, into a multitude of subsamples in a stepwise manner on the basis of a recursive application of log-$t$ regression tests. The mechanism

11. Since the convergence hypothesis centers on the evolution of potential output rather than on the deviations from it, we follow PS and use the HP-filtered output data after removing the cyclical components. According to PS, the log-$t$ regression test has a decent discriminatory power against club convergence alternatives.

12. PS (2009) have implemented their techniques to find evidence of convergence in income per capita among the 48 U.S. states over 1929–1998. Their analysis, however, is subject to the aforementioned limitation of deflating nominal income by national CPIs without accounting for cross-state price differences.

**FIGURE 5**
Relative Transition Paths of State Real Output per Worker

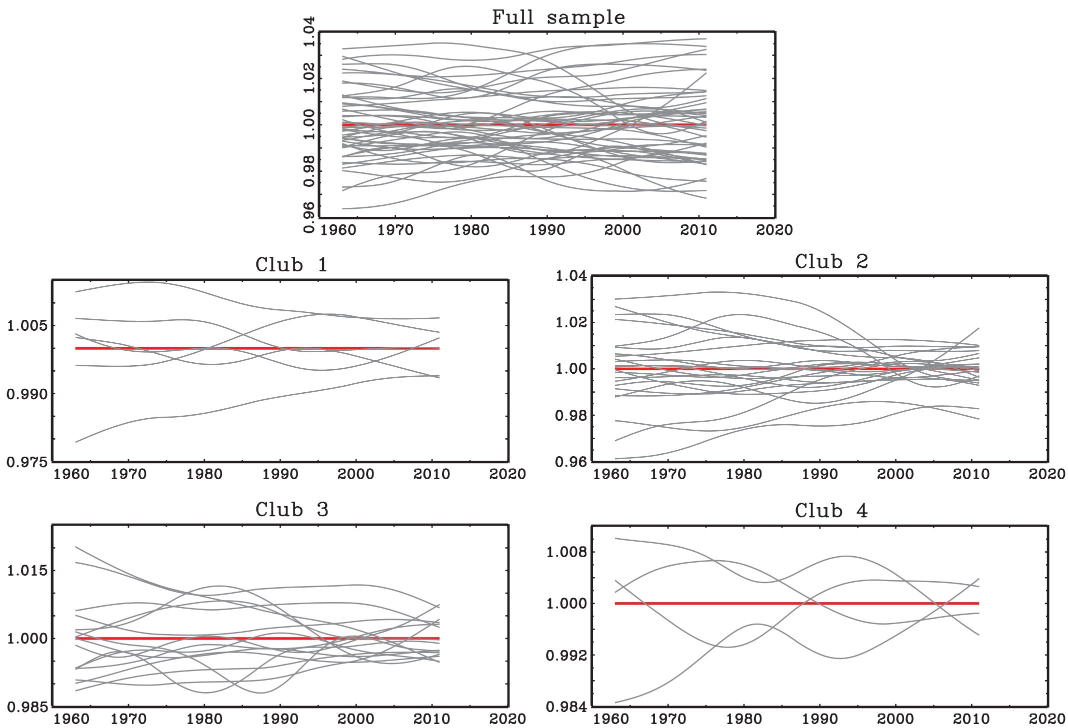



**TABLE 2**
Log-*t* Convergence Test and Convergence Clubs

| | Log-*t* Test | Constituent States | Average Productivity Nominal | Average Productivity Real |
|---|---|---|---|---|
| Full sample [48] | −0.545* (0.039) | ALL | 38,158 | 50,201 |
| Club 1 [6] | 0.312* (0.081) | CA, CT, DE, MA, NJ, NY | 49,952 | 65,214 |
| Club 2 [23] | 0.547* (0.092) | AZ, CO, FL, GA, IL, IN, LA, MD, MI, MN, NV, NH, NC, OR, PA, RI, SC, SD, TN, TX, VA, WA, WY | 40,111 | 52,811 |
| Club 3 [15] | 0.173* (0.085) | AL, AR, ID, IA, KS, KY, ME, MO, NE, NM, OH, OK, UT, VT, WI | 35,281 | 46,373 |
| Club 4 [4] | 0.581* (0.068) | MS, MT, ND, WV | 31,994 | 42,097 |

*Note*: Figures in the parentheses and the square brackets, respectively, represent standard errors and the number of states in a group.
* denotes statistical significance at 5% level.

consists of several steps: (1) order the entire sample based on the final period output per worker; (2) select a core primary group based on the log-*t* regression test; (3) add new series to the core group in a sequential manner and run the log-*t* test until a subgroup is found within which the log-*t* test does not reject the null of convergence; (4) repeat this procedure until the remaining series do not contain any convergence subgroup.

Table 2 reports the results of the clustering algorithm which detects four different clubs of convergence. The point estimates of $\gamma$ in each club are positive and statistically significant, pointing toward convergence at the subgroup level. The clubs appear to be formed in the order of average level of real output per worker, with the highest for Club 1 and the lowest for Club 4.[13] Table 2 also lists the names of states belonging to each club. Club 1 includes six states that form a core primary group that passed the clustering test before others. Except for CA, all the states in Club 1 are located in the east and are recognized as traditionally rich states. Since these relatively richer states constitute the first club, our result here lends credence to the view that economic growth in the past several decades might have favored those states that were already relatively rich and hence increased inequality among states. Club 2 is the largest subgroup encompassing 23 states that accounts for the largest share of the nation's population and production. Compared to the first club, however, this club is quite heterogeneous not only in terms of geographical location, from NH in the Northeast to WA in the West, but also in terms of average output level. Club 3 is the second largest subgroup with 15 states that are geographically scattered as well. Club 4 comprises only four states that are conventionally recognized as low-income states. Overall, it is hard to relate the composition of clubs to the geographical location as there is little systematic pattern of geographical distribution of states within a convergence club as displayed in Figure 6.

To ensure that the formation of clubs is well grounded, we run a couple of robustness checks. A quick robustness check would be to look at the RTP of state output in each club. As displayed in the four lower panels of Figure 5, the transition curves in each club are clearly converging toward unity, reflecting convergence of output toward its own cross-sectional average. This is in stark contrast to the case of the full sample we have seen earlier. Figure 7 provides another piece of evidence on the robustness of our club formation. We apply two popular methods of testing convergence, β- and σ-convergence, to the real output of states in each club. If the clustering mechanism works properly within the conventional framework, one may expect to see the evidence of convergence within clubs but not across clubs. The left-hand panel in Figure 7 displays strong evidence of β-convergence in each club as the fitted line of the scatterplot clearly shows an inverse relationship between initial output level (on the horizontal axis) and average output growth rates (on the vertical axis). Note that states in Club 1 are clustered in the upper-right corner, while states belonging to Club 4 are in the lower-left corner. This implies that the states in Club 1 not only had higher initial output levels, but also experienced faster output growth compared to those in Club 4, leading to divergence between the two clubs. A similar story is told from the right-hand panel of Figure 7 which shows compelling evidence of σ-convergence at the club level. Output dispersion appears to have declined over time in each club, whereas it has risen substantially for the full sample around the mid-1970s. As such, both popular measures of output convergence reach an agreement that output convergence in the United States has proceeded among the subsets of states for the last several decades. It seems natural to ask, then, what characteristics do the member states in the same club share which are distinctive from those of the other clubs. We will pursue this issue in Section IV.

### *C. Theoretical Underpinnings on Club Convergence*

Our finding on the club convergence among U.S. states is compatible with the prediction of many theoretical models. Although originally emerging from empirical evidence,[14] the notion of club convergence has its theoretical underpinnings in both neoclassical and endogenous growth models. Galor (2010), for example, illustrates that club convergence is viable in the standard neoclassical growth models once they are augmented with empirically significant variables, such as human capital and capital market imperfections.[15] Club convergence is also accommodated within the framework of

13. One should be cautious in interpreting this as saying that club membership is purely governed by states' output level. As presented in Table 1, MA belongs to Club 1 even though its real output per worker is lower than that of LA which belongs to Club 2. Our analysis based on real per capita output data yields qualitatively similar results on the presence of club convergence, but with a difference in the composition of convergence clubs. Using output per capita data, we found three convergence clubs with somewhat different constituents. The results are not reported here, but are available upon request.

14. Since the finding by Baumol (1986) that clustering is an important feature of world income data, a number of studies (e.g., Dowrick and DeLong 2003; Durlauf and Johnson 1995; Quah 1996, to cite a few) have documented the evidence of club convergence, with different countries converging towards different steady states depending on their *structural* characteristics. A nonexhaustive list of structural characteristics includes technologies, preferences, population growth, government policy, factor market structure, and so on.

15. Galor (2010) contends that club convergence is more plausible than a conditional convergence hypothesis if economies that are identical in their fundamentals converge to the same steady-state level of output per capita regardless of their initial conditions.

**FIGURE 6**
Geographic Distribution of Convergence Clubs

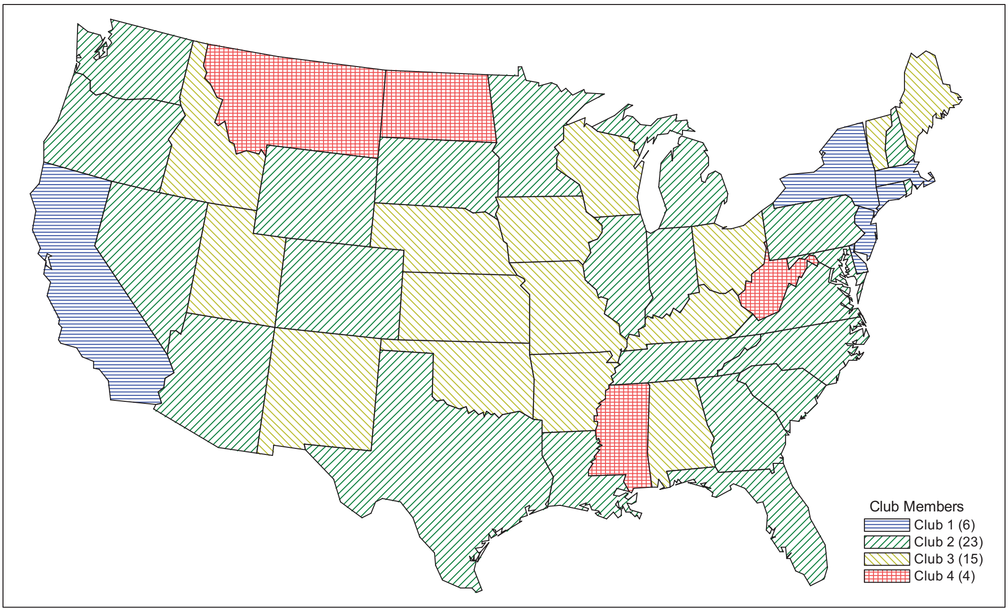
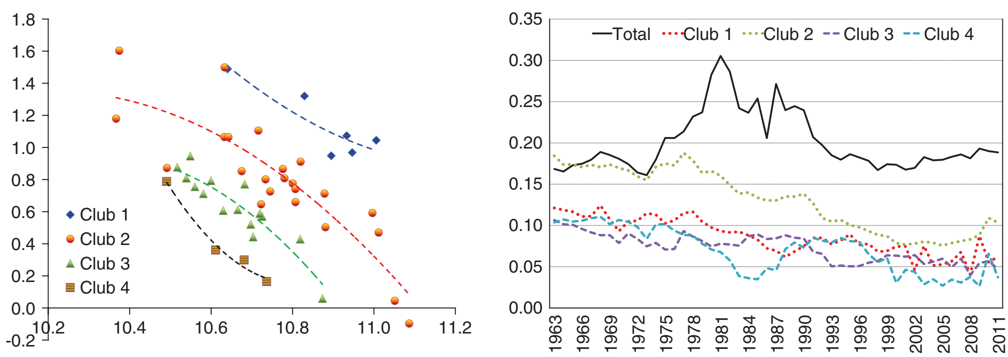



**FIGURE 7**
β- (on the Left) and σ-Convergence (on the Right) by Convergence Clubs




endogenous growth theories by differences in human capital or frictions in the diffusion of technological innovations across economies.[16]

16. While human capital has been emphasized in the first-generation endogenous growth models (e.g., Lucas 1988; Romer 1990) in which growth is assumed to be primarily driven by the economy-wide stock of human capital, the second-generation endogenous growth models (e.g., Aghion and Howitt 1998; Jones 1996; Vandenbussche, Aghion, and Meghir 2004) focus on the creation and diffusion of knowledge as the driving force of club convergence.

Theoretical exploration at the subnational level, however, has been rather limited. This is in large part due to the common perception that a much faster convergence can be achieved among regions within a nation with more homogeneous economic and institutional environments and lower barriers to factor mobility. As an important contribution along this line, Aghion et al. (2009) develop a multistate endogenous growth model which postulates that cross-state variation of economic growth in the United States is largely determined by a state's proximity to the technological frontier, which in turn depends on investments in education. The authors emphasize patenting and migration as important "intermediating variables" for the relationship between education and economic growth. More recently, Gennaioli et al. (2013b) present a modified version of the neoclassical model of regional growth in which highly persistent disparities in regional incomes and the consequent multiple growth regimes are attributed to a wide variation in barriers to factor mobility. As for the sources of limited factor mobility, they suggest (a) the intrinsic nontradeability of some factors or goods, such as land and housing; and (b) the presence of man-made barriers to factor mobility, such as policy and regulation. In their model, they have argued compellingly that human capital, using educational attainment as a proxy, is especially important in accounting for regional differences in both income and productivity. In fact, the related literature witnesses a growing body of empirical evidence suggesting that the presence of spatial frictions in knowledge transfer gives rise to a significant variation in the creation and diffusion of knowledge across regions within a nation (e.g., Hillberry and Hummels 2003; Glaeser and Kohlhose 2004).[17] Provided that production factors and knowledge do not move freely due to spatial frictions, technology creation and spillovers would be geographically localized and thus regional economies may evolve toward multiple steady states depending on the degree to which technology spillovers are locally appropriated.

As such, more recent theories of growth and development tend to focus on technology spillovers and human capital as the main driving forces behind regional output differences. Since the notion of club convergence is borne out by a variety of theoretical models, however, it seems improbable to pin down a single growth theory that can sufficiently explain why convergence clubs emerge among similarly situated subnational economies. Besides, there seems no clear consensus on which growth determinants ought to be included in such a growth model. As noted by Acemoglu (2009), for example, technology and human capital themselves could be influenced in some way by deeper variables, such as geography and institutions. Indeed, the fact that U.S. states, which are far more homogeneous than countries in terms of technological and productivity developments, have gone through different paths of output growth may lend credence to the view that institutional and policy differences play a crucial role in the observed club convergence patterns.[18] In a similar context, Mitchener and McLean (2003) have stressed institutional and geographical features as key determinants of differences in productivity levels across U.S. states. We therefore view that focusing on a specific theoretical model may not provide a full account of the formation of convergence clubs, although theoretical models provide useful guidance to the potential determinants of club formation. This renders us to resort to data-driven analysis in identifying the factors behind the formation of club convergence in the next section.

## IV. FACTORS RESPONSIBLE FOR THE CLUB CONVERGENCE

In this section, we implement a couple of regression analyses in searching for the potential factors that account for the formation and composition of convergence clubs observed in the data. Our first regression analysis is based on a discrete response model in which we link the estimated club membership of states to a host of state-level characteristics that have appeared relevant in the growth literature (e.g., Durlauf et al. 2006; Reed 2009). Due to the well-known endogeneity issue, however, the identified potential determinants are not much informative about the direction of causality. To address this issue, we carry out robust regression analysis using dynamic panel data estimation techniques.

17. In principle, there should be no friction in trade between U.S. states as it is unconstitutional to impede interstate commerce, but in practice it is hardly accepted that interstate distribution of goods and knowledge is totally frictionless. In a recent study, Allen and Arkolakis (forthcoming) maintain that geographic location alone accounts for a substantial fraction (about 24%) of the spatial variation in incomes across the United States.

18. Policies are institutional factors that involve the distribution of resources (e.g., tax rates) which eventually affect economic agents and their decision making. Differences across states in the degree of policy and regulation are known to be relevant for intrinsically nontradeable factors or goods, such as land and housing (e.g., Ganong and Shoag 2012). Although appealing at the intuitive level, institutional factors are hard to identify and measure in the data, especially at the subnational level. Nevertheless, it is often claimed that the effect of institutional and geographical characteristics has diluted over time, especially in the role of resource endowments which has become far less important in production after 1980 (e.g., Glaeser and Kohlhose 2004).

### A. Candidate Explanatory Variables

The literature is replete with candidate explanations for the composition of club convergence. Although there is no simple mapping between the factors that enhance output growth and the factors conducive to the formation of convergence clubs, the determinants of output growth could be relevant factors for club convergence so long as they vary systematically across clubs in such a way that they favor a specific group of states compared to others. Among the large number of potential determinants that were offered by many previous applications of growth regression to the presence of multiple growth regimes, we consider over 50 explanatory variables as candidates to investigate whether and how they account for the formation of convergence clubs.[19] The sources and descriptions of these candidate determinants are presented in Table A1. Following the guidance from theoretical work, we group them into several major categories: (1) technology; (2) education and human capital; (3) physical capital; (4) geographic and climatic characteristics; (5) institutional and policy characteristics; and (6) other characteristics including demography and industry structure. Most of these variables are available for the entire sample period of 1963–2011, but with different frequencies. While many of them have annual observations, some variables based on decennial census data (e.g., demographic variables) have at most five observations over the sample period.

### B. Ordered Logit Model

The ordered logit model permits us to assess the relative importance of potential explanatory variables by regressing them on the ordered structure of a state's club membership.[20] We consider the following ordered regression model

$$y_i = X_i\beta + \epsilon_i$$

where $y_i$ denotes state $i$'s membership in a certain club which is categorically coded as 1 for Club 1, 2 for Club 2, and so on. It should be noted that the numerical category is assigned in the opposite order of the corresponding average output level of clubs. Moreover, the numerical value of dependent variable bears no quantitative meaning and thus the magnitudes of the corresponding coefficients are not straightforward to interpret. $X_i$ contains explanatory variables with a constant term. Because of the limited cross-sectional dimension ($N = 48$), we set the maximum number of explanatory variables to seven in each regression exercise.

Table 3 summarizes the ordered regression results for coefficient estimates and standard errors in seven different model specifications which are selected based on the values of log-likelihood. In each specification, all of the included explanatory variables are statistically significant in combination and separately. Among a set of potential factors suggested in the literature (e.g., Durlauf et al 2006; Reed 2009), our econometric analysis identifies 12 strong explanatory variables on states' club memberships: *PATENTS*, *COLLEGE*, *FINANCE*, *EDUPROD*, *EDUEXP*, *HEALTH*, *MIGRATION*, *INEQUALITY*, *DENSITY*, *INFLATION*, *EFI*, and *FDIGSP*, whose detailed descriptions are relegated to Table A1.

Among them, the strongest evidence is found for three variables, *PATENTS*, *COLLEGE* and *FINANCE*, as they appear significant in each model specification. The significance of *PATENTS* and *COLLEGE* is consistent with the prevailing view established in the theoretical literature that economic growth has been predominantly driven by technology and human capital. As an indicator of state's ability to innovate new products and production techniques, *PATENTS* is significant in determining state's club membership probably through diverging effects of the creation and exploitation of knowledge exerted on the interstate output distribution. Negative signs of the coefficient estimates imply that states with higher level of innovative activities are likely to join Club 1, which on average experience higher levels of output per worker. Also known as a proxy measure of distance to the technological frontier, *PATENTS* reflects the level of technology to which states have access. States producing more (per capita)

19. Durlauf et al. (2006) list 145 regressors that have been found to be statistically significant in a number of growth studies based on conventional standards. Many of them are not relevant for the analysis of intranational growth. See also Reed (2009, Table 1) for a long list of variables that were adopted by many previous studies on U.S. state economic growth.

20. This approach is appropriate for our analysis because the dependent variable, club membership, is ordinal in a couple of senses. First, the four convergence clubs may have a well-defined ordered structure because the PS (2007) clustering mechanism is designed to sort out subgroups in an ordinal manner by its convergence speed. Second, the identified clubs are roughly in line with the level of output per worker. States with a relatively high output per capita tend to cluster to Club 1, while states with a lower output per worker fall into Club 4.

**TABLE 3**
Ordered Logit Estimation Results

| Regressors | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| *patents* | −0.02* | −0.03* | −0.02* | −0.02* | −0.02* | −0.02* | −0.02* |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| *college* | −0.38* | −0.32* | −0.30** | −0.33* | −0.31* | −0.77* | −0.46* |
| | (0.16) | (0.14) | (0.16) | (0.16) | (0.15) | (0.29) | (0.21) |
| *finance* | −0.90* | −0.87* | −1.17* | −1.56* | −2.31* | −1.69** | −2.07* |
| | (0.44) | (0.44) | (0.56) | (0.70) | (0.79) | (0.80) | (0.44) |
| *eduprod* | −0.49* | −0.46* | | | | | |
| | (0.20) | (0.20) | | | | | |
| *eduexp* | 0.01* | 0.01* | | | | | |
| | (0.00) | (0.00) | | | | | |
| *diversity* | −21.12** | | | | | | |
| | (12.20) | | | | | | |
| *health* | | −0.01** | | | −0.01* | | |
| | | (0.01) | | | (0.00) | | |
| *migration* | | | | −0.44* | −0.32** | | |
| | | | | (0.16) | (0.18) | | |
| *inequality* | | | −103.83* | | | −327.57* | −199.76* |
| | | | (43.01) | | | (111.16) | (60.25) |
| *density* | | | −2.28* | −2.78* | −2.40* | | −3.81* |
| | | | (0.72) | (0.80) | (0.81) | | (1.23) |
| *inflation* | | | 4.58* | 3.95* | | | |
| | | | (2.04) | (1.81) | | | |
| *EFI* | | | | | −3.81* | −2.71* | |
| | | | | | (1.31) | (1.31) | |
| *fdi/gsp* | | | | | | −0.59* | −0.65* |
| | | | | | | (0.27) | (0.22) |
| Log-likelihood | −26.14 | −26.16 | −20.94 | −20.21 | −20.19 | −17.52 | −16.44 |
| $\chi^2$ (d.f.) | 65.97 | 65.94 | 76.38 | 77.84 | 77.89 | 78.52 | 80.70 |
| Prob > $\chi^2$ | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Pseudo $R^2$ | .5578 | .5575 | .6458 | .6582 | .6586 | .6914 | .7105 |

*Notes*: See Table A1 for the definitions of each explanatory variable.
* (**) denotes statistical significance at 5% (10%) level. Standard errors are reported in parentheses.

patents are likely to be closer to the technological frontier and hence have more innovation-driven industries that lead to higher relative output per worker. Aghion et al. (2009), for instance, maintain that cross-state variation of economic growth in the United States is largely determined by a state's proximity to the technological frontier, proxied by patents. To the extent that frontier technologies are constantly improving through patents, states with a larger stock of patents are presumed to be more innovative in creating new products and production techniques and thus achieve a higher productivity.

The significance of *COLLEGE* is not surprising in view of the fact that innovative activities are contingent on the stock and quality of human capital as more educated population can enhance the ability of learning and adoption of new innovations in technologies.[21] The negative sign for *COLLEGE* implies that states with a higher proportion of the population with a college degree are more likely to belong to Club 1, probably because innovative activities require a higher level of knowledge stock accumulation. Typically measured by the fraction of people that has attained a certain schooling level, human capital has been central to the theories of endogenous growth (e.g., Lucas 1988) and is empirically found to have a significant and positive effect on the long-run growth path of technology. More recent studies (Gennaioli et al. 2013a) tend to stress the importance of differences in human capital quality in accounting for intranational variation in output per worker. Vandenbussche et al. (2004) document that the growth effects of primary and secondary education are insignificant while that for higher education is significantly positive. Our result lends credence to this view as we fail to find any significance for another measure of educational attainment, *HIGHSCHOOL*, which is the fraction of the population that has graduated from at least high schools. That is, the contribution of human

21. Human capital affects output not only directly as it enters the production function as an input in growth models, but indirectly as it contributes to higher technological progress by facilitating innovation and diffusion of new technologies.

capital to the growth of output and productivity depends critically on the types and levels of human capital. While human capital affects both innovation and imitation, output growth is mainly driven by innovations by highly educated people rather than by imitations by unskilled human capital. In this vein, interstate differences in higher educational attainment may have exerted a diverging effect on output distribution across states. The impact of educational attainment on economic growth could have strengthened after the 1980s with the inception of the information era and the rise of the IT industry due to their more human capital-intensive character (e.g., Oliner and Sichel 2000).

Another variable that is significantly related to the composition of convergence clubs is *FINANCE* which measures the share of the finance industry in a state's output. The negative coefficient of this variable implies that states with an industrial base that is more concentrated in the finance industry are more likely to belong to Club 1, consistent with the well-established positive impact of financial development on economic growth (e.g., Levine 2005). A more developed financial system tends to spur economic growth by promoting efficient allocation of resources and a rapid accumulation of capital through diversification of risks. At the regional level, Gennaioli et al. (2013b) argue that financial development can account for cross-state patterns of regional income disparities.

For the other nine variables, their estimated coefficients have the expected signs except for *EDUEXP* (i.e., negative for *INFLATION* and positive for the remaining eight variables). It is reassuring to note that a negative sign indicates that states belonging to Club 1 have a higher level in terms of the corresponding characteristic compared to those in Clubs 2–4. Consequently, states with higher labor productivity in education sector, higher diversified industrial structure, a more per capita spending on health by government, a higher level of income inequality, a higher density of population, a greater level of economic freedom (or less government intervention and regulation), and a higher FDI-GSP ratio, are more likely to be a member of Club 1, whereas states in Club 4 are likely to have higher inflation rates. The negative sign of *INEQUALITY* corroborates the finding by Partridge (2005) on the positive relationship between income inequality and economic growth. This suggests that income inequality in the United States might have proceeded across states as well as within each state. The significance of variable *FDIGSP* confirms the general view on the positive role of FDI in economic growth. The industrial structure (*DIVERSITY*) also enters with the expected negative signs, in accordance with the widely agreed positive effect of diversified industry structure on economic growth.

The public finance variables, however, have mixed results on explanatory power. While state and local governments' spending on health (*HEALTH*) appears to have an influence on states' club membership, state governments' expenditures on public infrastructure, such as highway capital, do not. Another public finance variable, *EDUEXP*, is statistically significant but enters with an unexpected positive sign. Since the positive sign of the variable suggests that states with a larger government spending on education (or investment in education) are more likely to join Club 4 than Club 1, it is counter-intuitive and contradicts the well-established empirical regularity on the positive correlation between education spending and economic growth. A plausible explanation for this, however, can be found from the negative sign of the *MIGRATION* variable. To the extent that highly educated workforce in poorer states with more spending on education migrate into richer states with a lower investment in education (out-migration from poorer states and in-migration to richer states), education spending in the poor states is enhancing economic growth not in the poorer states but in the richer states.

When it comes to the significance of the so-called *deeper* explanatory variables, some policy-related institution variables, such as government expenditure on health and education, and economic freedom, have explanatory power on the club membership of states, but no strong evidence is found for geographic or climatic characteristics of states.

### *C. Endogeneity and Dynamic Panel Data Analysis*

While our regression analysis in the previous section identified a handful of state-level characteristics as potential determinants of club formation, the results do not necessarily establish the direction of causality due to the well-known problem of endogeneity. Put differently, the correlation found in the regression analysis may simply reflect associative links or even reverse causation if both dependent variable and explanatory variables are jointly determined by a third variable or if explanatory variables are themselves functions of the dependent variable. Since the four convergence clubs are formed in such a way that is roughly related to the level of output per worker, this issue is particularly relevant to some of our regressors such as *COLLEGE* and *FINANCE* that are likely affected by states' economic conditions and hence output level (e.g., Bils and Klenow 2000; Durlauf et al. 2006).[22] In empirical growth research, a popular approach to dealing with the endogeneity problem has been to implement difference- and system-generalized method of moments (GMM) estimators (e.g., Arellano and Bond 1991; Arellano and Bover 1995) which involve using instruments to control for unobserved heterogeneity and simultaneity. The basic idea of GMM estimators is to exploit the dynamic nature of growth models by utilizing lagged variables as instruments. As documented in more recent studies (e.g., Bazzi and Clemens 2013; Durlauf et al. 2006), however, use of the GMM estimators is not desirable if instrumental variables are either invalid or weak, or both, as often is the case in the growth literature. An alternative strategy we consider here is the recursive mean adjustment (RMA) method proposed by Choi et al. (2010) who show that the RMA strategy is useful in reducing bias in the estimation of linear dynamic panel data models. As highlighted by Choi et al. (2010), the RMA estimator is straightforward to implement and is more practically appealing than GMM/IV estimators in the presence of weak moment conditions. Moreover, it is shown that the RMA estimator performs well in terms of reducing bias even when error terms are cross-sectionally dependent.

In this section, we adopt both the dynamic panel GMM estimators and the RMA estimator to probe the causal links between output per worker and the key determinants identified in the previous section, after accounting for the endogeneity issue. Specifically, we consider the following prototypical dynamic panel data model,

(4)
$$y_{it} = \sum_{j=1}^{p} \alpha_j y_{i,t-j} + X_{it}\beta + W_{it}\gamma + \tau_t + \nu_i + \epsilon_{it},$$

which can be rewritten as

(5)
$$\Delta y_{it} = \left(\alpha_1 - 1\right) y_{i,t-1} + \sum_{j=2}^{p} \alpha_j y_{i,t-j} + X_{it}\beta + W_{it}\gamma + \tau_t + \nu_i + \epsilon_{it},$$

where $y_{it}$ is log output per worker at state $i$ in year $t$, $X_{it}$ is a set of exogenous regressors, $W_{it}$ is a vector of endogenous regressors, $\tau_t$ represents time-specific effects, $\nu_i$ denotes state-specific effects, and $\epsilon_{it}$ is an error term. This specification allows us to address the question of whether endogenous variables ($\boldsymbol{W}$) have an economically and statistically significant causal effect on $y$, while holding $X$ constant. Beware that by design the lagged dependent variables ($y_{i,t-j}$) are correlated with the unobserved fixed effects ($\nu_i$), giving rise to bias and inconsistency of estimators. The inclusion of time dummies ($\tau_t$) is to capture unobserved cross-sectional dependence across state output which is correlated through common national shocks. In our regression exercise, this term is removed by using cross-sectionally demeaned data for all variables. Since our purpose here is to examine the direction of causality, we focus on the three most significant explanatory variables that were found in our ordered logit model analysis, *PATENTS*, *FINANCE*, and *EDUPROD*, in which annual observations are available for the entire sample period.[23]

Table 4 presents the regression results. In the GMM estimation, all three explanatory variables are treated as potentially endogenous variables. Nonetheless, the estimation results are qualitatively very similar in both GMM and RMA estimators as the coefficient estimates enter the regressions with the same signs. The variable *PATENTS* enters the regressions significantly in all specifications with an expected positive sign. That is, *PATENTS* exerts a positive impact on output per worker, leading states with higher level of patents to Club 1, even after controlling for the potential endogeneity of regressors. By contrast, the evidence for the other two regressors is not much compelling. While the point estimate is unexpectedly negative for *FINANCE*, it

22. In their influential work, Bils and Klenow (2000) argue that the ample correlational evidence between education and economic growth may represent a reverse causality as higher output growth can lead to higher levels of education.

23. Though *COLLEGE* is another significant variable, it is not considered here because the data are available only decennially. For this reason, we use *EDUPROD* as a replacement. As a matter of fact, a similar problem of data constraint exists in many other variables identified as being important by the ordered logit model.

**TABLE 4**
Dynamic Panel Estimation

| Regressors | DIFF-GMM | SYS-GMM | RMA |
|---|---|---|---|
| $y_{t-1}$ | −0.0993‡ | −0.0495‡ | −0.0077‡ |
| | (0.0106) | (0.0071) | (0.0031) |
| *PATENT* | 0.0005‡ | 0.0004‡ | 0.0004‡ |
| | (0.0002) | (0.0002) | (0.0002) |
| *FINANCE* | −0.7736‡ | −0.6781‡ | −0.9365‡ |
| | (0.1871) | (0.1727) | (0.1903) |
| *EDUPROD* | 0.0010 | 0.0012 | 0.0005 |
| | (0.0010) | (0.0011) | (0.0010) |
| Sargan test ($p$ value) | .4235 | .3568 | |

*Note*: The regression equation is

$$\Delta y_{it} = \sum_{j=1}^{p} \alpha_j y_{i,t-j} + \boldsymbol{W}_{it}\gamma + \nu_i + \epsilon_{it},$$

where $y_{it}$ denotes output per worker in state $i$ in year $t$ and $\boldsymbol{W}_{it}$ is a vector of explanatory variables that are treated as endogenous. The Stata commands, *xtabond* and *xtabond*2, are used for the GMM estimation. Both $y_{it}$ and $W_{it}$ are cross-sectionally demeaned to remove unobserved fixed effects. The Sargan test has the null hypothesis that the instruments used are not correlated with the residuals.
‡ denotes statistical significance at 1% level. Entries in parentheses represent robust standard errors.

is positive but insignificant for *EDUPROD*.[24] To sum, our dynamic panel data analysis suggests *PATENTS* as the most consistently significant causal factor affecting club formation.

### *D. Technology Progress and Club Convergence*

Our result on the strong significance of *PATENTS* in explaining the formation of convergence clubs poses a challenge for the conventional assumption that technology and human capital have virtually unlimited mobility across state borders.[25] In the absence of barriers to the mobility of technology and human capital, diffusion of technology, and knowledge should facilitate convergence among states, because states that are further behind the technology frontier experience a more rapid growth due to lower costs of adopting new technology as stipulated in the "advantage of backwardness." If the mobility of technology and factors is spatially limited or localized, however, cross-state differences in the technology level may generate diverging patterns of output per worker across states. Cross-state variation in human capital composition can further promote economic clustering of states with persistently different levels of output because off-frontier states do not have sufficient levels of human capital to take advantage of new technology developed on the frontier. In fact, in addition to earlier evidence on localized technology spillovers (e.g., Jaffe et al. 1993), more recent studies (e.g., Belenzon and Schankermanz 2013; Ganong and Shoag 2012; Smith 1999) have found compelling evidence that the mobility of human capital and technology spillovers within the United States are far from frictionless. Analyzing knowledge spillovers at the state level using state patent grants as a proxy, for example, Smith (1999) finds that the interstate knowledge spillovers within the United States are geographically localized and exert a diverging effect on cross-state standards of living. Belenzon and Schankermanz (2013) also document the relevance of state borders in the diffusion of knowledge from universities as citations to patents are strongly constrained by state borders.

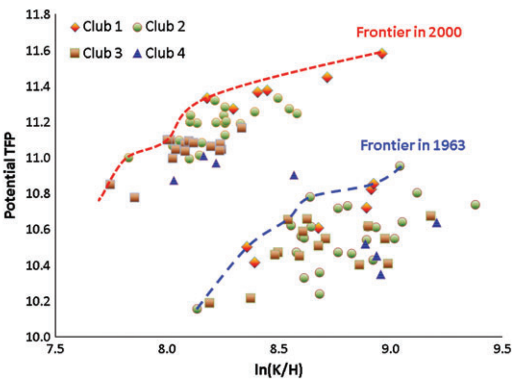
To elucidate how frictions in technology spillovers could lead to the clustering of states with different levels of output per worker, we estimate the U.S. production frontier using a nonparametric deterministic frontier approach called data envelopment analysis (DEA). The basic idea of the DEA approach is to construct an efficient production frontier taking physical capital ($K$) and human capital ($H$) as inputs without assuming any specific functional form. The associated efficiency levels of individual states are then measured by distances from the frontier.

Figure 8 plots the estimated technology frontier and the actual output per worker of 48 states given factor combination ($K/H$) for the year 1963 and 2000 using the dataset constructed by Turner et al. (2006). We first note that there are nonuniform technological frontiers across U.S. states as some states are on the efficient frontier, while many others are below it. More importantly, states in different convergence clubs tend to have significantly different levels of technology. Take the frontier in year 2000 for instance, states belonging to Club 1 (represented in diamonds) are either on the frontier or very close

24. The unexpected negative sign of FINANCE can be explained by the fact that the dynamic panel techniques look at dynamic, rather than static, relationship over time. We notice that on average states with a higher share of finance industry have a higher level of output per worker, but states with a faster growth in the share of finance industry do not necessarily experience a faster growth of output per worker.

25. Our result also suggests that physical capital has little explanatory power on the formation of clubs probably due to its relatively low barriers to mobility (e.g., Gennaioli et al. 2013b; Tamura 2012).

**FIGURE 8**
Technology Frontier of U.S. States in 1963 and 2000




to it, whereas states in Club 4 (represented in triangles) remain far below the frontier, implying that technology differences could be an important source of club convergence. The nonuniform technological frontiers suggest that although the United States as a whole has always been on the world technology frontier (WTF) (e.g., Jerzmanowski 2007), this is less likely the case at the state level in light of the considerable cross-state heterogeneity in technology level. The cross-state heterogeneity can also be seen in the evolution of the technology frontier over time. The upper-leftward shift of the frontier line indicates a nonneutral technological progress during the period 1963–2000, with a smaller physical-human capital ($K/H$) ratio accompanied by a faster human capital accumulation. Notice that technological progress has slightly different implications for different clubs. Whereas states in Clubs 2–4 have made human capital-intensive technological progress judging from the upper-leftward shift, states in Club 1 have made factor-neutral technological progress between 1963 and 2000 in view of the upward shift, or stable $K/H$ ratios. This is perhaps because states in Club 1 concentrate more on innovating new technology than adopting it, as evidenced by larger average per capita patents, and hence operate effectively with less human capital relative to other states. Our results, therefore, can be interpreted as saying that the club convergence found in the U.S. state output data is driven by this nonneutral technological progress that may have been relatively more beneficial for the originally wealthy and physical-capital-rich states.

To further probe this issue, we estimate average TFP growth and decompose it into technological progress and changes in technological efficiency by convergence clubs. The results are presented in Table 5. Contrary to our prior expectations, it is not Club 1 but Club 3 which experienced the fastest growth in TFP. While Club 3 states experienced an annual TFP growth of 0.12% on average, TFP has grown in Club 1 at the rate of just 0.02% per year.[26] Not surprisingly, Club 4 had the slowest TFP growth in the sample period. The story changes somewhat dramatically when we look at the TFP growth decomposed into technological progress and technological catch-up (or efficiency change) for a given set of inputs. As reported in Column 2, Club 1 states had the fastest technological progress at the rate of 0.09% per year but with the slowest speed of improvement in efficiency, whereas states in Club 3 experienced the fastest rate of efficiency gain (i.e., catching up). Combined together, the faster overall TFP growth of states in Clubs 2 and 3 relative to those in Club 1 was mainly driven by improvements in efficiency rather than in technological progress. In other words, the TFP growth comes largely from technological change in high-income states (i.e., by pushing the technological frontier outward), but from catching up to the frontier in lower income states. It is worth noting that states in Club 4 experienced comparable improvements in efficiency to those in Club 3, but the contribution of efficiency gain was outpaced by the decline in technological progress. As a result, the technological gap between states in Club 1 and states in Club 4 has further widened during the sample period under study. Given that the formation of club convergence is more closely related to the speed of technological progress than efficiency improvements, we reckon that what matters for a state's standard of living is its ability to develop technological innovations

26. The slower TFP growth in Club 1 states relative to those in Clubs 2 and 3 is somewhat surprising in light of the well-known positive impact of TFP on output growth. One possible explanation is that the DEA result is based on data up to 2000, whereas our analysis on convergence club was conducted using data set covering until 2011. Our DEA analysis therefore could not account for important changes in the dynamics of output data occurring in the last 11 years. An alternative explanation is that in the DEA analysis we measure human capital as average years of schooling in the labor force for each state. But, it is now widely agreed that composition of human capital has a vital effect on TFP growth in the sense that skilled human capital is important for *innovation*, while unskilled human capital for *imitation*. This composition effect of human capital is not considered in the analysis.

**TABLE 5**
Malmquist Index of TFP Growth and Its Components by Clubs

| | TFP Growth | Efficiency Change | Technical Progress |
|---|---|---|---|
| Club 1 | 1.0002 | 0.9993 | 1.0009 |
| Club 2 | 1.0010 | 1.0007 | 1.0004 |
| Club 3 | 1.0012 | 1.0010 | 1.0002 |
| Club 4 | 0.9965 | 1.0008 | 0.9958 |

rather than its capacity to adopt technologies already developed in other states.

## V. CONCLUDING REMARKS

The progress of output convergence among the continental U.S. states has been very different since the 1970s. After a century-long process, output convergence is no longer an adequate description of the growth pattern for the U.S. states since the mid-1970s when the overall convergence process came to a halt. From a welfare point of view, this discontinuity of the output convergence process may have an important implication, particularly in relation to the ample empirical evidence on the income-consumption inequality nexus.[27] Furthermore, whether or not output converges over time bears a crucial policy implication in that policy measures are often justified by their ability to reduce output differences across subeconomies within a nation.

This paper reexamined the process of output convergence in the United States for the last five decades by taking a novel approach to investigating this long-standing issue. We first utilized *real* output per worker data that was generated using state-specific price levels instead of a national price level, which most studies in the literature so far have failed to do because of the lack of a proper measure of state-level price data. In addition, we employed the convergence test developed by PS that is designed to capture the observed nonlinear and time-varying dynamics of output data. We found no evidence of overall convergence among the 48 continental U.S. states. But our clustering mechanism unveils that output convergence has proceeded among states within certain subgroups into which states are grouped by dynamic behaviors of real output per worker.

Using a regression analysis based on discrete dependent models, we identified a set of state-level characteristics that account for the formation of convergence clubs. Among them, variables related to technology and knowledge, such as per capita patents and educational attainment, stand out. States with larger stocks of patents or higher portions of college graduates have achieved higher levels of productivity, possibly because they are closer to the technological frontiers and hence are more innovative in creating new products and production techniques. On one hand, our empirical finding supports the prediction of recent theories of growth and development that technology and human capital are the key determinants of regional output differences. On the other hand, our result suggests that states in different convergence clubs are sufficiently disparate in terms of technology level and technological changes, casting doubt on the empirical relevance of the common view that the interstate flow of knowledge and factors is frictionless in the United States. The persistent cross-state differences in output per worker is driven by the fact that a productivity-enhancing technological innovation in one state does not flow quickly enough to other states, possibly due to the factors that limit relocation of resources. In fact, our analysis of frontier approach suggests nonuniform technological frontiers across U.S. states, which may have different implications for different states. We posit that the impact of technological progress on output growth became stronger after 1980 with the inception of the information era and the rise of the IT industry due to their more knowledge- and human-capital-intensive nature.

There are some potential policy lessons to draw from our study. If intranational inequality across individuals is due in large part to cross-state difference as in the case of the international counterpart (e.g., Schultz 1998), policy efforts to reduce individual output inequality within countries could be effective by mitigating cross-state output differences. The analysis here emphasizes the importance of specific policies toward technology and human capital improvements. State-level policies to promote knowledge accumulation may exert a crucial impact on economic growth mainly through productivity-enhancing technological innovations. At the national level, policies to improve the diffusion of knowledge and human

27. According to Attanasio et al. (2012), the rise in income inequality since the 1980s has translated to an increase in actual well-being inequality by increasing consumption inequality.

capital will help reduce the cross-state output inequalities. Our results also provide some useful insights on the future progress of output convergence in an existing monetary or fiscal union, such as the European Monetary Union. Although it is widely believed that membership in such a union would promote convergence across member countries, the debate is far from settled on its long-term effect. In view of the experience of the U.S. states that have long been consolidated fiscally as well as monetarily, the discontinuity of output convergence among its subeconomies hints that a centralized federal authority with a well-integrated market may not necessarily achieve a long-run convergence in output among its member economies, particularly in the presence of frictions in the flow of knowledge and production factors.

## APPENDIX: DESCRIPTION OF EXPLANATORY VARIABLES

**TABLE A1**
List of Explanatory Variables Considered in Regression Analysis

| Variable | Description | Source |
|---|---|---|
| *AVGTAX* | Average state income tax rate [1969–1998] | Crain (2003) |
| *CAPSTOCK* | Per capita capital in millions of dollars [1963–2000] | Turner et al. (2006) |
| *CLIMATE* | Average annual number of cooling degree days [1992–2010] | NOAA website |
| *COLLEGE* | Average percent of persons 25 years and above who have attained a bachelor's degree | Census Bureau |
| *DECENTRAL* | Share of total state and local government expenditure made by local government | Census Bureau |
| *DENSITY* | Average population per square miles | Census Bureau |
| *DEPENDENCY* | Average ratio of the combined under 18 and 65 and above populations to the 18 to 64 population | Census Bureau |
| *DIVERSITY* | Industry diversity measured by $\sum_i$(Earnings in industry $i$/Total Earnings)$^2$ | Census Bureau |
| *EDUEXP* | Per capita expenditure on education as a share of total local and state government expenditures | Census Bureau |
| *EDUPROD* | Labor productivity in education industry | Census Bureau |
| *EFI* | State-level economic freedom index [1981–2008] | Heckelman (2013) |
| *FDIGSP* | Foreign direct investment (the gross book value in current dollars of property, plant, and equipment of affiliates in all industries) as a percent of GSP [1977–2008] | BEA |
| *FEDEMP* | Share of total employee by Federal employee | Census Bureau |
| *FEDGOVT* | Share of total earnings by Federal government | Census Bureau |
| *FINANCE* | Share of F.I.R.E. industry in terms of the number of establishments | Census Bureau |
| *HEALTH* | Per capita expenditure on health and hospitals as a share of total state and local government expenditures | Census Bureau |
| *HIGHINST* | Number of higher education institutions per million people | Census Bureau |
| *HIGHSCHOOL* | Average percent of persons 25 years and over who have graduated from high school | Census Bureau |
| *HIGHWAY* | Per capita expenditure on highways as a share of total state and local government expenditures | Census Bureau |
| *INEQUALITY* | Average top-decile income share (in %) | Frank (2009) |
| *INFLATION* | State inflation rate based on GSP deflator | BEA |
| *LATITUDE* | Latitude for the centroid of each state | |
| *MARTAX* | Marginal state income tax rate [1969–1998] | Crain (2003) |
| *MIGRATION* | Total net migration rate (%) | Census Bureau |
| *MIGRCOL* | Net migration rate (%) of young college graduates | Census Bureau |
| *NORTHEAST* | Regional dummy for states in Northeast | |
| *PATENTS* | Average patents granted per million residents | Patent and Trademark Office |
| *PRODUCTIVITY* | Labor productivity in each industry for nine large industrial classifications | Census Bureau |
| *SOUTH* | Regional dummy for states in South | |
| *STATEGOVT* | Share of total earnings by state and local government | Census Bureau |
| *STRUCTURE1* | Share of each industry in terms of the number of establishments: (1) Agriculture; (2) Mining; (3) Construction; (4) Manufacturing; (5) Transportation, Communication, Utilities; (6) Wholesale; (7) Retail; (8) F.I.R.E.; (9) Service | Census Bureau |
| *STRUCTURE2* | Share of each industry in terms of total earnings in nine large industrial classifications | Census Bureau |
| *TAXBUR* | Total state and local tax revenues as a share of personal income | Census Bureau |
| *URBANIZATION* | Percentage of urban population | Census Bureau |

## REFERENCES


Acemoglu, D. *Introduction to Modern Economic Growth*. Princeton, NJ; Oxford: Princeton University Press, 2009.

Aghion, P., L. Boustan, C. Hoxby, and J. Vandenbussche. "The Causal Impact of Education on Economic Growth: Evidence from US." Harvard University, Mimeo, 2009.

Aghion, P., and P. Howitt. *Endogenous Growth Theory*. Cambridge, MA: MIT Press, 1998.

Allen, T., and C. Arkolakis. "Trade and the Topography of the Spatial Economy." *Quarterly Journal of Economics*, forthcoming.

Arellano, M., and S. Bond. "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies*, 58(2), 1991, 277–97.

Arellano, M., and O. Bover. "Another Look at the Instrumental Variable Estimation of Error Components Models." *Journal of Econometrics*, 68, 1995, 29–51.

Attanasio, O., E. Hurst, and L. Pistaferri. "The Evolution of Income, Consumption, and Leisure Inequality in the U.S., 1980-2010." National Bureau of Economic Research Working Papers No. 17982, 2012.

Barro, R. J. "Economic Growth in a Cross-Section of Countries." *Quarterly Journal of Economics*, 106, 1991, 407–43.

Barro, R. J., and X. Sala-i-Martin. "Convergence." *Journal of Political Economy*, 100, 1992, 223–51.

———. *Economic Growth*. 2nd ed. Cambridge, MA: MIT Press, 2004.

Bauer, P. W., and Y. Lee. "Estimating GSP and Labor Productivity by State." Federal Reserve Bank of Cleveland Policy Discussion Papers 16, 2006.

Bauer, P. W., M. E. Schweitzer, and S. Shane. "State Growth Empirics: The Long-Run Determinants of State Income Growth." Federal Reserve Bank of Cleveland Working Paper Series No. 06-06, 2006.

Baumol, W. "Productivity Growth, Convergence and Welfare." *American Economic Review*, 76, 1986, 1072–85.

Bazzi, S., and M. A. Clemens. "Blunt Instruments: Avoiding Common Pitfalls in Identifying the Causes of Economic Growth." *American Economic Journal: Macroeconomics*, 5(2), 2013, 152–86.

Belenzon, S., and M. Schankermanz. "Spreading the Word: Geography, Policy and Knowledge Spillovers." *Review of Economics and Statistics*, 95, 2013, 884–903.

Berry, W. D., and R. C. Fording. "An Annual Cost of Living Index for the American States, 1960-95." *Journal of Politics*, 60, 2000, 550–67.

Bils, M., and P. Klenow. "Does Schooling Cause Growth?" *American Economic Review*, 90, 2000, 1160–83.

Carlino, G. A., and L. Mills. "Are U.S. Regional Incomes Converging? A Time Series Analysis." *Journal of Monetary Economics*, 32, 1993, 335–46.

Chen, L.-L., S. Choi, and J. Devereux. "Have Absolute Price Levels Converged for Developed Economies? The Evidence since 1870." *Review of Economics and Statistics*, 90(1), 2008, 29–36.

Choi, C. Y. "A Reexamination of Output Convergence in the U.S. States: Toward Which Level(s) Are They Converging?" *Journal of Regional Science*, 44(4), 2004, 713–41.

Choi, C. Y., N. C. Mark, and D. Sul. "Bias Reduction in Dynamic Panel Data Models by Common Recursive Mean Adjustment." *Oxford Bulletin of Economics and Statistics*, 72(5), 2010, 567–99.

Choi, C. Y., and Y.-K. Moh. "How Useful Are Tests for Unit-Root in Distinguishing Unit-Root Processes from Stationary but Nonlinear Processes?" *Econometrics Journal*, 10, 2007, 82–112.

Crain, W. M. *Volatile States: Institutions, Policy, and Performance of the American States*. Ann Arbor, MI: University of Michigan Press, 2003.

Del Negro, M. "Asymmetric Shocks among U.S. States." *Journal of International Economics*, 56, 2002, 273–97.

Dowrick, S., and J. B. DeLong "Globalization and Convergence," in *Globalization in Historical Perspective*, edited by M. D. Bordo, A. M. Taylor, and J. G. Williamson. Chicago: University of Chicago Press, 2003, 191–220.

Durlauf, S., and P. A. Johnson. "Multiple Regimes and Cross Country Growth Behaviour." *Journal of Applied Econometrics*, 10(4), 1995, 365–84.

Durlauf, S., P. A. Johnson, and J. R. Temple "Growth Econometrics," in *Handbook of Economic Growth*, Vol. 1A, edited by P. Aghion and S. Durlauf. Amsterdam: Elsevier Science, 2006, 555–677.

Evans, P., and G. Karras. "Do Economies Converge? Evidence from a Panel of U.S. States." *Review of Economics and Statistics*, 78, 1996, 384–8.

Fan, J., and I. Gijbels *Local Polynomial Modelling and Its Applications*. London: Chapman and Hall, 1996.

Frank, M. W. "Inequality and Growth in the United States: Evidence from a New State-level Panel of Income Inequality Measures." *Economic Inquiry*, 47(1), 2009, 55–68.

Galor, O. "The 2008 Lawrence R. Klein Lecture—Comparative Economic Development: Insights from Unified Growth Theory." *International Economic Review*, 51(1), 2010, 1–44.

Ganong, P., and D. Shoag. "Why Has Regional Convergence in the U.S. Stopped?" Harvard Kennedy School, Mimeo, 2012.

Gennaioli, N., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. "Human Capital and Regional Development." *Quarterly Journal of Economics*, 128(1), 2013, 105–64.

———. "Growth in Regions." National Bureau of Economic Research Working Paper No. 18937, 2013.

Glaeser, E. L., and A. Saiz. "The Rise of the Skilled City." *Brookings-Wharton Papers on Urban Affairs*, 2004, 2004, 47–105.

Glaeser, E. L., and J. E. Kohlhose. "Cities, Regions and the Decline of Transport Costs." *Papers in Regional Science*, 83, 2004, 197–228.

Heckelman, J. C. "Income Convergence among U.S. States: Cross-Section and Time Series Evidence." *Canadian Journal of Economics*, 46(3), 2013, 791–1155.

Henderson, D. J., C. Papageorgiou, and C. F. Parameter. "Growth Empirics without Parameters." *Economic Journal*, 122, 2012, 125–54.

Henriksen, E., F. E. Kydland, and R. Sustek. "Globally Correlated Nominal Fluctuations." National Bureau of Economic Research Working Papers No. 15123, 2009.

Hillberry, R., and D. Hummels. "Intranational Home Bias: Some Explanations." *Review of Economics and Statistics*, 85(4), 2003, 1089–92.

Jaffe, A. B., M. Trajtenberg, and R. Henderson. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics*, 108(3), 1993, 577–98.

Jerzmanowski, M. "TFP Differences: Appropriate Technology vs. Efficiency." *European Economic Review*, 51(8), 2007, 2080–110.

Jones, C. I. "Time Series Tests of Endogenous Growth Models." *Quarterly Journal of Economics*, 110(2), 1996, 495–525.

Kalemi-Ozcan, S., A. Reshef, B. E. Sørensen, and O. Yosha. "Why Does Capital Flow to Rich States?" *Review of Economics and Statistics*, 92(4), 2010, 769–83.

Levine, R. "Finance and Growth: Theory and Evidence," in *Handbook of Economic Growth*, Vol. 1, edited by P.

Aghion, and S. Durlauf. Amsterdam: Elsevier Science, 2005, 865–934.

Lucas, R. "On the Mechanics of Economic Development." *Journal of Monetary Economics*, 22(1), 1988, 3–42.

Mitchener, K. J., and I. W. McLean. "U.S. Regional Growth and Convergence, 1880–1980." *Journal of Economic History*, 59(4), 1999, 1016–42.

———. "The Productivity of U.S. States since 1880." *Journal of Economic Growth*, 8(1), 2003, 73–114.

Oliner, S. D., and D. E. Sichel. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives*, 14(4), 2000, 3–22.

Partridge, M. D. "Does Income Distribution Affect U.S. State Economic Growth?" *Journal of Regional Science*, 45(2), 2005, 363–94.

Phillips, P. C. B., and D. Sul. "Transition Modelling and Econometric Convergence Tests." *Econometrica*, 75, 2007, 1771–855.

———. "Economic Transition and Growth." *Journal of Applied Econometrics*, 24, 2009, 1153–85.

Quah, D. "Empirics for Economic Growth and Convergence." *European Economic Review*, 40(6), 1996, 1353–75.

Reed, W. R. "The Determinants of U.S. State Economic Growth: A Less Extreme Bounds Analysis." *Economic Inquiry*, 47(4), 2009, 685–700.

Romer, P. "Human Capital and Growth: Theory and Evidence." *Carnegie-Rochester Series on Public Policy*, 32, 1990, 251–86.

Schultz, T. P. "Inequality in the Distribution of Personal Income in the World: How It Is Changing and Why." Economic Growth Center, Yale University, Discussion Paper No. 784, 1998.

Shintani, M. "A Nonparametric Measure of Convergence towards Purchasing Power Parity." *Journal of Applied Econometrics*, 21, 2006, 589–604.

Smith, P. J. "Do Knowledge Spillovers Contribute to U.S. State Output and Growth?" *Journal of Urban Economics*, 45, 1999, 331–53.

Tamura, R. "Development Accounting and Convergence for US States." Clemson University, Mimeo, 2012.

Turner, C., R. Tamura, S. E. Mulholland, and S. Baier. "Education and Income of the States of the United States: 1840–2000." *Journal of Economic Growth*, 12, 2006, 101–58.

Vandenbussche, J., P. Aghion, and C. Meghir. "Growth and the Composition of Human Capital." *Journal of Economic Growth*, 11(2), 2004, 97–127.

Young, A. T., M. J. Higgins, and D. Levy. "Sigma Convergence versus Beta Convergence: Evidence from U.S. County-Level Data." *Journal of Money, Credit and Banking*, 40(5), 2008, 1083–93.