What Do Cross-Sectional Growth Regressions Tell Us about Convergence?

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Abstract:

This paper tests the dynamic implications of beta-convergence with time-series data from the 48 contiguous U.S. states. The motivation for this paper rests with the interpretation of results from cross-sectional growth regressions. These results show that poor regions experience faster per-capita income growth than rich regions. This is interpreted as evidence of convergence. However, convergence is a dynamic adjustment process with testable implications in time-series data, while the literature employs cross-sectional data to estimate this dynamic concept. A set of strong assumptions must be made to jump from this cross-sectional correlation to its interpretation as a speed of convergence. We find that the time-series properties of the data appear to be inconsistent with beta-convergence dynamics. Further, our analysis rejects the assumptions necessary to interpret the cross-sectional correlation as a speed of convergence. Therefore, our results call into question the interpretation that has been placed on this important cross-sectional finding.

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I. Introduction

Cross-sectional growth regressions show that poor regions grow faster than rich regions in per-capita income. This result has been interpreted as evidence of convergence. But, doesn't this cross-sectional result also imply that the richer a region becomes (i.e.: as the region converges), its per-capita income growth rate will diminish over time? In other words, convergence is a dynamic process that should be observable in time-series data. That question provides the motivation for this paper, which tests the dynamic implications of convergence with time-series data.

The regression coefficient summarizing the cross-sectional relationship mentioned above has been interpreted as the dynamic speed of adjustment to the steady state of a growth model *exhibiting diminishing returns to capital* (exogenous as well as some endogenous growth models). By the definition of equilibrium, if a steady state exists, then differences from it must diminish over time -- an adjustment process called conditional convergence. With additional assumptions a stronger form of convergence emerges -- convergence means that per-capita incomes will converge to the same level across regions. The strong form of convergence directly predicts that poor regions will grow faster than rich regions. But, if we are able to control for the variation in steady states across regions, then even the weaker form of conditional convergence predicts this cross-sectional result.

For these reasons, the convergence properties of growth models have been used to explain cross-sectional results. In contrast, endogenous growth models with non-diminishing returns to capital cannot explain this result. Therefore, the estimated cross-sectional relationships are taken to be direct evidence in support of convergence and against this class of endogenous growth models. This study addresses a deficiency in this interpretation. Convergence is a dynamic process of adjustment to a steady-state equilibrium. Some very restrictive assumptions are necessary in order to make the leap from cross-sectional correlation to interpretation as a dynamic speed of adjustment.

Because convergence is a dynamic concept, time-series information should contain evidence of this adjustment process. If time-series data display little evidence of convergence dynamics, then we would conclude that the assumptions required to link dynamic adjustment behavior to the observed cross-sectional correlation had been violated. Furthermore, this finding would call into question the interpretation of this important cross-sectional finding. We perform statistical tests of the assumptions using time-series data from the 48 contiguous U.S. states. It is generally presumed that distinctions between the weak form and the strong form of convergence are unnecessary in these data. We find that the time-series properties of the data appear to be inconsistent with this presumption, the set of restrictive assumptions, and with the presence of convergence dynamics.

The remainder of this paper is organized as follows. In section II, we present a review of the literature along with a regression that demonstrates cross-sectional convergence for the 48 U.S. states. In section III, we present the dynamic framework for the convergence process that has been labeled beta-convergence; contrast this with the cross-sectional implementation of the model; and discuss the assumptions necessary to make them equivalent. The results of the statistical tests are presented in section IV. We offer some concluding remarks in section V.

II. Literature Review

Recent interest in the convergence hypothesis began with two papers by Moses Abramovitz (1986) and William Baumol (1986). Employing O.E.C.D productivity data from a cross-section of countries that spans a century (1870 to 1979), Baumol (1986) noticed an inverse correlation between initial productivity levels (c. 1870) and long-run productivity growth rates averaged over this time span. However, he also cautioned against taking this correlation too seriously and proceeded to list a whole series of caveats.

Follow-up work by Wolff (1991), Dowrick and Nguyen (1989), and Mankiew, Romer, and Weil (1992) focused on linking the empirical cross-section relationship to the convergence properties of growth models. Barro (1991), Barro and Sala-i-Martin (1991, 1992) also elaborate this linkage. Their work added a new twist. Barro and Sala-i-Martin confirmed Baumol's finding that this cross-sectional correlation did not consistently appear in international data. However, they found that adding a few "conditioning" variables to the regression leads to an inverse partial correlation that appears consistently. They associated this partial correlation with the concept of conditional convergence.

Barro and Sala-i-Martin (1991, 1992) showed that the cross-sectional relationship between initial per-capita income and the per-capita income growth rate held consistently without the use of conditioning variables in U.S. state-level data. They assert that this relationship is consistent with conditional convergence. However, when conditioning variables are included in their regressions, they found that their proxies for the steady state exhibited little variation across the states. This suggests, albeit very cautiously, that the estimated cross-sectional relationship may be consistent with unconditional convergence, hence the presumption that distinguishing between conditional and unconditional convergence is unnecessary with U.S. state-level data. An example of this unconditional relationship using U.S. state-level data over the time period from 1948 to 1996 is presented in Figure 1.

Recent work in the cross-sectional growth literature adds new conditioning variables (Becsi (1996)), extends the model though sectoral disaggregation (Bernard and Jones (1996)), tests for measurement error (Dowrick and Quiggen (1997)), and extends the analysis to additional data sets (see the literature reviewed by Sala-i-Martin (1996)).

III. Beta-Convergence: Theory and Critique

3.1 Theory and Critique

The concept underlying the interpretation of the cross-sectional correlation between initial productivity levels and the long-run growth rate is the idea of a dynamically stable steady-state equilibrium. By definition, when a steady state is stable, non-steady-state productivity levels will dynamically converge to the steady state through an equilibrating mechanism that results from the existence of diminishing returns to capital. Two different types of adjustment processes are possible: deterministic or stochastic. Beta-convergence is a deterministic adjustment process, formally presented in equations (1a and 1b) and in (2a) [2].

$$(1a)\ \frac{\partial y}{\partial t} = \gamma - \beta(y - \bar{y})$$

$$(1b)\ \frac{\partial \bar{y}}{\partial t} = \gamma$$

The adjustment process defined in equation (1) says that the instantaneous rate of growth in productivity is the exogenous rate of technological change less a constant proportion of the difference of productivity from the steady-state equilibrium. The coefficient, β, is the speed of adjustment and is also termed the speed of convergence.

In equation (1), y represents the log of productivity, $\bar{y}$ represents the log of steady-state productivity, and γ represents the exogenous rate of Harrod-neutral technical change. If β is positive, then the steady state is dynamically stable (i.e.: positive differences are forced to converge downward toward the steady state, while negative differences are forced to converge

[2] Convergence should be in levels rather than log-levels. The time path of y(t) in levels (as given by equation (2a)) would be altered by geometric growth in $\bar{y}_t$ rather than linear growth. However, the time-series dynamics of the growth rate (the variable of interest) is highly nonlinear, resulting in a complex expression for equation (2b). For expositional purposes, we employ the log-linear approximation used in the literature. However, the arguments, results, and conclusions expressed in this paper are unaffected by this difference (see Appendix 3).

upward toward the steady state). On the other hand, if β is negative, then the steady state is dynamically unstable (i.e.: positive differences are forced to be larger and negative differences are forced to be more negative, implying an ever-greater divergence from the steady state).

Equation (1) is a non-stochastic differential equation. The solution to this differential equation gives the non-stochastic dynamic time path of productivity. The solution is given in both log-levels and log first-difference forms in equations (2a and 2b) below. These equations are superscripted by (i) to denote being only one part of a multi-economy system.

$$
\begin{gathered}
(2a)\quad y_t^i = \bar{y}_t^i + e^{-\beta^i t}(y_0^i - \bar{y}_0^i) \\
(2b)\quad \Delta y_t^i = \gamma^i + \lambda^i (y_0^i - \bar{y}_0^i) e^{-\beta^i t} \\
\forall\, i = 1, \dots, n \\
\text{with} \\
\lambda^i = (1 - e^{\beta^i}) \\
\bar{y}_t^i = \bar{y}_0^i + \gamma^i t
\end{gathered}
$$

As before, y represents the log of productivity; $\bar{y}$ represents the log of steady-state productivity; and y_0 represents the log of the initial period productivity level. The dynamic convergence process in equations (2a and b) is illustrated in Figure 2.

The dynamic nature of these equations should be readily apparent. For any individual economy, equation (2b) shows that convergence dynamics are represented by a nonlinear, deterministic time trend. If we add a stochastic disturbance term to equation (2b), statistical estimation of the convergence dynamics would require a time series of growth rates, a time trend, and an estimate of the initial difference of productivity from its steady state -- in other words, time-series rather than cross-sectional data.

Equation (2b) represents the weak form of conditional beta-convergence. There are 2n restrictions that must be imposed on equation (2b) in order for the strong form of unconditional convergence in productivity or, equivalently, per-capita incomes to occur: all n economies must have the same initial steady-state $\bar{y}_0$ and the same exogenous growth rate of technological change, γ (see assumption [b] below).

Let's contrast this with the cross-sectional equation estimated in the literature. The starting point is equation (2a), the dynamic time path of productivity in levels. For a sample of T-time periods (0,....,T), take the difference equation over the T periods and calculate its average, dividing by T. This average T- period difference is presented in equation (3a).

$$(3a)\quad \frac{1}{T}(y_T^i - y_0^i) = \gamma^i - b^i(y_0^i - \bar{y}_0^i)$$
$$\text{where}:$$
$$b = \frac{(1 - e^{-\beta^i T})}{T}$$

The equation actually estimated in the literature is listed in equation (3b). In order to estimate beta from a cross-section of U.S. states, certain restrictions must be imposed on equation (3a) in order to obtain the estimating equation (3b). The two sets of restrictions are the following:

[a] The speeds of convergence are equal: $\beta^i = \beta$, $\forall i = 1,\ldots,n$.

[b] Unconditional convergence occurs. The initial steady states: $\bar{y}_0^i = \bar{y}_0$, and the exogenous growth rates are equal: $\gamma^i = \gamma$, $\forall i = 1,\ldots,n$.

With these restrictions, $b * \bar{y}_0$ can be subsumed into the constant term of the equation, yielding:

$$(3b)\quad \frac{1}{T}(y_T^i - y_0^i) = a - b\,y_0^i$$
$$\text{where}:$$
$$a = \gamma + b\,\bar{y}_0$$
$$b = \frac{(1 - e^{-\beta T})}{T}$$

One additional requirement is necessary in order to interpret estimated cross-sectional relationships as evidence of convergence. This requirement concerns the informational content of the dependent variable. If the convergence dynamics represented by equation (2b) occur, then:

[c] The average rate of growth contains information on both a deterministic adjustment process **and** an exogenous rate of growth, so that:

$$\frac{1}{T}\left(y_T^i - y_0^i \right) \equiv \gamma + \lambda\delta\left[y_0^i(\tau_0^i) - \bar{y}_0(\tau_0^i) \right]$$
$$where:$$
$$\lambda = (1 - e^{\beta})$$
$$\delta = \sum_{t=1}^{T} \frac{e^{-\beta t}}{T}$$

For a derivation of this expression, see Appendix 2. This average growth rate is a constant for each observation. Let's explore cross-sectional variation in the dependent variable as well as the dynamic implications of this expression. If we sample the cross-section at the same point in time, but along different convergent paths (i.e.: $\tau^i = \tau$), then as y_0^i increases across regions, the average growth rate becomes smaller—giving us the inverse correlation found in the literature. In this case, both assumption [a] and assumption [b] are necessary to identify equation (3b) when estimating b.

The average growth rate expression also includes dynamic implications. Assume that the convergence path is the same for all observations. Then cross-sectional sampling means that we observe the economies at different points in time along this convergent path (i.e.: at different τ^i's). As y_0^i increases across regions, both the difference from steady state and the average growth rate become smaller (due to the convergence dynamics) – which also gives us the inverse correlation found in the literature. In this case, all three requirements guarantee that cross-sectional variation mimics the time-series dynamics, ensuring the proper interpretation of a regression estimate of b as a speed of convergence.

Now let's assume that deterministic convergence dynamics do not occur. Because $\beta = 0$, then λ would equal zero, and the average growth rate measures the exogenous rate of technological change along with some possible stochastic variation that may not have been completely averaged out. In this situation, cross-sectional regression estimates of b would be spurious and could not be interpreted as the speed of convergence, β.

3.2 Open Economy Considerations

The theory outlined in the previous section assumes that each region operates as a closed economy. For the U.S. states, this is obviously not a reasonable assumption. In this section, we discuss open economy considerations for the convergence model.

Resource mobility has implications for convergence. With identical technologies across regions, if either physical capital or labor is perfectly mobile across regions, then unconditional convergence is instantaneous. Factor price equalization rather than diminishing returns to capital provides the equilibrating force for convergence. But, if capital or labor is partially immobile, diminishing returns to capital continues to provide the equilibrating force for convergence (see Barro and Sala-i-Martin (1995) for this conclusion). However, openness increases the speed of convergence.

Empirically, perfect resource mobility would devastate both cross-sectional and time-series estimates of convergence dynamics from growth models. With perfect mobility, convergence via factor price equalization occurs immediately, so that time-series data would exhibit no evidence of convergence dynamics. Similarly, since convergence does not occur through the growth model mechanism, cross-sectional data would violate the informational requirements of the dependent variable, making any estimated relationship suspect.

What is the evidence on labor mobility? Numerous studies (see Newman (1982), Crandall (1988), Sahling and Smith (1983)) have confirmed the presence of significant regional wage differentials that persist for very long periods of time, suggesting that labor is not perfectly mobile. However, the evidence concerning the reasons for the differentials is inconclusive. Some studies (Browne (1980), Gerking and Weirick (1983), Farber and Newman (1989)) conclude that regional wage differentials result from compensation of differences in regional amenities. When this is taken into account, regional wage differences are eliminated. However, other studies (Farber and Newman (1987), Krueger and Summers (1988), Dickens and Katz (1987)), suggest that the differentials result from persistent inter-industry wage differentials, due to regional specialization in different industries. Barro and Sala-i-Martin (1991) and Braun (1993) present evidence on the responsiveness of migration to regional income differentials, which suggests sluggish movement. On the whole, the evidence appears to imply less than perfect labor mobility.

What is the evidence on capital mobility? While financial capital is perfectly mobile within national borders, it is not clear that physical capital is equally mobile. The movement of physical capital across regions occurs through investment. Cross-state evidence of instantaneous adjustment in investment behavior would provide indirect evidence on physical capital mobility. Rickman, Shao, and Treyz (1993) estimate a stock adjustment model of investment behavior, in which investment results from a difference between actual capital stocks and optimal capital stocks. He estimates the model with pooled time-series cross-section data from the U.S. states. He finds a very small stock adjustment coefficient, suggesting high costs of adjustment. Adjustment costs would act as a barrier to the movement of capital across regions. Barro, Mankiw, and Sala-I-Martin (1992) provide some additional evidence that capital mobility is less than perfect. Therefore, the evidence suggests that open economy considerations would not harm estimation of the convergence behavior of growth models with U.S. state-level data.

IV. An Empirical Test of the Assumptions

We start with a test of the informational content of the dependent variable. Our strategy is to test for the presence of a deterministic trend in the first differences of per-capita incomes. If this time-series is mean stationary, with no evidence of a trend, then the data stochastically vary about the exogenous growth rate (γ) so that the informational requirement of assumption [c] has been violated. However, equation (2b) shows that if beta-convergence dynamics are present, then the first differences should contain a non-linear deterministic trend that asymptotically approaches the exogenous growth rate. In this situation, the first differences will not be mean-stationary and will satisfy the informational requirement of assumption [c]. Because the initial difference from the steady-state enters equation (2b) only as a scaling factor, a seemingly simple test of this assumption [c] is whether the first differences of per-capita incomes are mean stationary, or trend stationary.

The length of the data span is also important to the extent that finding assumption [c] to be false may still be consistent with convergence, if beta-convergence had already taken place prior to the sample period, or if convergence follows some alternative process. Employing a sufficiently long data span for this test should eliminate the possibility of beta-convergence having occurred prior to the start of the sample.

While a simple test for a trend in the first differences of per-capita incomes on a long enough data span may be sufficient to establish the presence of beta-convergence dynamics, it is not able to differentiate between conditional and absolute beta-convergence. However, the test of assumption [b] is dependent upon the results of the trend test of first differences. If a trend is present, the asymptotic value that is approached by the trend represents the exogenous growth rate. Finally, provided that a statistical test validates assumption [c], direct estimation of equation (2b) using the entire panel of data along with a test of the restriction of equal betas would be sufficient to establish assumption [a].

We first test the validity of assumption [c]. The results of our test of this assumption are presented in Tables 1 and 2. Table 1 presents unit root tests of the first differences of quarterly per-capita incomes for each of the 48 contiguous U.S. states over the time period from 1948 to 1996, and for the U.S. as a whole over the time period 1890 to 1997. Table 1 lists both Dickey-

Fuller and augmented Dickey-Fuller t-tests of the AR(1) coefficient.[3] These results strongly reject the presence of a unit root, implying that the first differences are stationary.

Table 2 presents the results of three different tests for the presence of a deterministic trend in the first differences of cyclically adjusted quarterly data.[4] The columns list: (a) the estimates of a linear trend, (b) the estimates of a nonlinear quadratic trend, and (c) the estimates of a nonlinear hyperbolic trend. The results in Table 2 are unable to reject the hypothesis of mean stationary first differences. Because of the possibility of a type II error, assumption [c] can only be weakly rejected. But, this rejection also suggests that we may not be able to interpret the cross-sectional estimate of the relationship between initial per-capita income and the per-capita income growth rate as a speed of convergence, when estimated over this time-span with these data.

The rejection of assumption [c] implies that the time-series data are not consistent with the presence of convergence dynamics, but this could be due to instantaneous convergence occurring as a result of perfect resource mobility. If convergence occurs through immediate cross-border movement of resources, then per-capita income would always be at its steady-state value. Furthermore, in order for perfect resource mobility to explain this result we need to find evidence that convergence is unconditional. Therefore, a test of assumption [b] is particularly relevant.

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[3] All results were estimated using quarterly per-capita personal income. The BEA compiles a quarterly personal income series. The BLS collects population data on an annual basis. We use per-capita incomes because a sufficiently long series of productivity data using BEA's GSP data is not available. GSP data is considered to be useful for periods after 1977 providing only seventeen years of information. While the BEA also has annual per-capita incomes starting in 1929, we do not include this longer period because of possible structural breaks during the Great Depression (1929 to 1940) and World War II (1940 to 1945).

[4] The data contain heteroscedasticity and cyclical variation. The heteroscedasticity appears as shifts in variance over time. Cyclical variations are irregular with respect to amplitude and duration. Since we are interested in long-term properties, we cyclically adjust the data using a decomposition method. The results in Table 2 are estimated from the de-cyclicalized data. Standard-errors and t-statistics are presented in heteroscedasticity consistent form. Future versions of this paper anticipate correcting for heteroscedasticity and using an alternate cyclical adjustment procedure: *Hamilton's markov regime-switching method.*

The fact that the first differences are mean stationary suggests that growth of per-capita income during this time period was determined either by the long-run process of exogenous technical change, or by some endogenous growth mechanism. Any convergence dynamics are either the result of factor price equalization, or achieved through a relatively short-run stochastic adjustment process. Therefore, it does not matter whether convergence had already taken place, or results from an alternative process. The observed per-capita income levels would contain information concerning the supposedly unobservable steady state, and simple trend estimation in levels via either a linear deterministic trend or a stochastic trend will extract the growth path of steady-state productivity levels.

On the other hand, if convergence never takes place, then the process driving growth is endogenous and concern about an unobservable steady state is misplaced. Simple trend estimation will show whether regions or states share the same endogenous growth paths and whether or not leapfrogging rather than convergence to the same level is possible.

Since the choice in estimating a deterministic or stochastic trend concerns the issue of whether the productivity levels are stationary, we do not concern ourselves with this issue here (see Swaine (1998) for details on the stochastic convergence hypothesis). To test assumption [b], we estimate a deterministic linear trend in per-capita income levels. The test for assumption [b] is that these trends are common (i.e.: identical) across the cross-section.

Table 3 presents the results from a panel estimation of a linear deterministic trend. These results strongly reject the equality restrictions of assumption [b] imposed on the coefficients across the cross-section. Therefore, two of the three assumptions that are necessary to interpret the cross-sectional correlation between initial per-capita income and its growth rate as a speed of convergence have been rejected, and with data for which unconditional convergence is assumed most likely to exist. Furthermore, with the rejection of assumption [b], we can reject perfect resource mobility as an explanation for the lack of convergence dynamics in the time-series data. If perfect resource mobility caused these results, then unconditional convergence would occur instantaneously and we would be unable to reject the equality restrictions of assumption [b]. Assumption [a] cannot be tested because with the rejection of both assumptions [b and c] the data are not consistent with beta-convergence dynamics occurring during this time span.

While we are unable to find the presence of beta-convergence dynamics in the post-war state-level data, the qualifier *a sufficiently long data span* still hangs over our analysis. To investigate the effect of this qualifier on our analysis, we present yet another test. Baumol et al. (1991) in *Productivity and American Leadership: The Long View*, provide an illustration of annual U.S. productivity growth from 1890 to 1969 in their Figures 2.1 and 4.1. These data, compiled by John Kendrick, show productivity growth that averages 2 percent over this time span, with the graph clearly showing no evidence of a trend. These data are indexed so that 1958 is equal to 100. We collect more current productivity data from the U.S. Bureau of Economic Analysis for the years 1958 to 1997, and then multiply Kendrick's data series by the 1958 value, in order to create a very long productivity data series spanning 108 years from 1889 to 1997.

The results of our analysis of this data, adjusted for two structural breaks (in 1934 and again in 1974), are included in Tables 1 and 2. These results span a period that includes the long process of large-scale industrialization in the United States (with the exception of the first 20 years of industrialization from 1870 to 1890). The results show that the data exhibit no discernible trend and lend further weight to our state-level results that the time-series evidence is inconsistent with the presence of beta-convergence dynamics. Finally, to any skeptics who object to adjusting for structural breaks, we present supplementary results in the Appendix, along with a discussion of our analysis of these supplementary results.

Because the time-series evidence is inconsistent with dynamic predictions from the beta-convergence model, we conclude that deterministic convergence dynamics are unable to explain the cross-sectional results reported in the literature (and the results that we presented for this same data set in Figure 1). For this reason, we conclude that the estimated cross-sectional correlation should not be interpreted as a dynamic speed of convergence. However, our results do not necessarily reject the convergence hypothesis. The time-series properties of our data may be consistent with stochastic convergence (see Swaine (1998) for evidence on this hypothesis). On the other hand, the mean-stationary property exhibited by our data is also consistent with the AK class of endogenous growth models (see Barro and Sala-i-Martin (1995)).

V. Conclusions

In this paper we tested the assumptions that are necessary to interpret the cross-sectional correlation between initial per-capita income and its growth rate as a dynamic speed of convergence. Our results suggest that the two most critical assumptions are the informational content of the per-capita income growth rate, and whether or not the steady-state growth paths are identical. The informational content assumption determines whether the long-run growth rate contains information concerning adjustment dynamics, or just a long-run exogenous growth process. Our test of this assumption suggests that the data are inconsistent with the presence of beta-convergence dynamics.

Since adjustment dynamics, if any exist, are relatively short-run, then per-capita income data in levels would contain information concerning the unobservable steady state. Estimating a trend in the levels should obtain the steady-state growth path. A test for identical trend equation coefficients (i.e.: a common trend) is also rejected for the U.S. states, violating the unconditional convergence assumption. This result also ensures that the test for informational content was not contaminated by perfect resource mobility.

The sum total of these results should call into question the appropriateness of interpreting the estimated cross-sectional relationship as a speed of convergence. Our results do not imply that convergence does not occur, only that the time-series evidence appears to be inconsistent with beta-convergence dynamics. Therefore, beta-convergence dynamics may not be able to explain this cross-sectional result. We conclude that the cross-sectional correlation is just that: a correlation -- and is still in search of an explanation.

Appendix 1

U.S. Productivity Growth (1890 to 1997)

In this appendix we present supplementary results in support of our adjustment for two structural breaks that we found to exist in the U.S. national productivity data. First, we should note that, a priori, three time periods could possibly contain structural breaks. These are the Great Depression, World War II, and the oil shocks of the 1970's.

To determine the presence of structural breaks, we first test for a non-stationary process. An augmented Dickey Fuller test including 4 lags cannot reject the presence of a unit root, suggesting that structural breaks may be present. Visual inspection of the data suggests two possible structural breaks. The first occurs in 1934 and lasts until the occurrence of the second in 1973-1974. To further investigate the presence of these breaks and their effects on any likely trend, we formally test the possibilities over different time spans.

We first test for the presence of any trend behavior during the 1890 to 1928 period. As Appendix Table 1 shows, we find no evidence of a trend during this time span. Next we examine the 1890 to 1973 period, where visual inspection suggests a break in 1934 that lasts until 1973. We find the presence of a statistically significant positive trend over this period. However, when we include a dummy variable for 1934 to 1973 along with the trend, the slope of the trend changes from positive to negative. The coefficient on the dummy variable is statistically significant, while the coefficient on the trend is not. Therefore, we conclude that the positive trend is picking up the effects of the structural break. After adjustment for the break, we find no evidence of a trend during this longer time span (1890 to 1973), which also happens to overlap part of the period contained in our state-level data (1948 to 1996).

Finally, we examine the full period from 1890 to 1997. With inclusion of the 1934 to 1973 dummy variable, we find the presence of a statistically significant negative trend over the time period from 1890 to 1997. But, since this result is not present during the preceding time intervals (1890 to 1973), then this trend must result from the well-documented productivity slowdown that occurred after 1973. Including a dummy variable for the 1974 to 1997 period in this regression finds that both the trend and the dummy become statistically insignificant (but with negative coefficients), implying that they are measuring the same thing. Therefore, we estimate a regression of productivity growth on the two dummy variables. A unit root test of the residuals from this regression strongly rejects non-stationary behavior (as shown in Table 1). We employ these residuals for the trend tests that are listed for the United States in Table 2.

Appendix Table 1 [a]
Trend Tests for US Productivity Data (1890 - 1997)

Time Period	Constant	Trend	Dummy 1933-1973	Dummy 1974-1997
1890-1928	0.02055300 (1.979184)	0.00002540 (0.056078)		
1890-1973	0.01585700 (2.478771)	0.00023800 (1.821964)		
	0.02241000 (3.107940)	-0.00017700 (-0.690113)	0.02331100 (1.870071)	
1890-1997	0.02745700 (4.749559)	-0.00012500 (-1.361189)		
	0.02335400 (4.321908)	-0.00022100 (-2.530778)	0.02522100 (4.464865)	
	0.02312800 (3.419365)	-0.00020900 (-0.882461)	0.02465200 (2.118334)	-0.00105800 (-0.056048)
	0.01842300 (4.431006)		0.01586900 (2.633827)	-0.01653200 (-2.362243)

a. t-statistics are in parentheses.

Appendix 2

Derivation of the informational Content of the Average Growth Rate

The proof of the expression contained in [c] is twofold. First, the average growth rate is identical to the average of the first differences. The proof of this proposition is relatively simple (for all y's except y_T and y_0 there is both a positive and a negative value for each time period, which cancel out in summation):

$$\frac{1}{T}\sum_{i=0}^{T-1}\Delta y_{T-i} \equiv \frac{1}{T}\left[(y_T - y_{T-1}) + (y_{T-1} - y_{T-2}) + \cdots + (y_2 - y_1) - (y_1 - y_0)\right] = \frac{1}{T}\left(y_T - y_0\right)$$

Using this identity, the second part of the proof derives from equation (2b).

$$(2b)\ \ \Delta y_t^i = \gamma^i + \lambda^i (\, y_0^i - \bar{y}_0^i \,)\, e^{-\beta^i t}$$
$$\forall\ i = 1, \dots, n$$
$$\text{with}$$
$$\lambda^i = (\, 1 - e^{\beta^i}\,)$$

If we apply assumption [a] and [b] to equation (2b), this reduces to:

$$\Delta y_t^i = \gamma + \lambda\, (\, y_0^i - \bar{y}_0 \,)\, e^{-\beta t}$$

Applying the summation operator to this expression yields:

$$\sum_{t=1}^{T}\Delta y_t^i = T\gamma + \lambda\, (\, y_0^i - \bar{y}_0\,)\sum_{t=1}^{T} e^{-\beta t}$$

Finally, dividing by T and substituting for the first part of the derivation results in [c].

$$\frac{1}{T}(\, y_T^i - y_0^i \,) \equiv \gamma + \lambda\delta\left[y_0^i - \bar{y}_0\right]$$
$$\text{where}:$$
$$\lambda = (1 - e^{\beta})$$
$$\delta = \sum_{t=1}^{T}\frac{e^{-\beta t}}{T}$$

Appendix 3

Convergence in Levels rather than in Log-Levels

For convergence in levels, the time path is given by a variant of equation (2a):

$$y_t^i = \bar{y}_0 e^{\gamma t} + e^{-\beta^i t}(\, y_0^i - \bar{y}_0^i \,)$$

In logs, this expression yields (because the log operator does not operate on a sum):

$$\ln y_t^i = \ln\left\{ \bar{y}_0 e^{\gamma t} + e^{-\beta^i t}(\, y_0^i - \bar{y}_0^i \,)\right\}$$

Finally taking the first difference of this expression yields the growth rate:

$$\Delta y_t^i = \ln\left\{ \bar{y}_0 e^{\gamma t} + e^{-\beta^i t}(\, y_0^i - \bar{y}_0^i \,)\right\} - \ln\left\{ \bar{y}_0 e^{\gamma t-1} + e^{-\beta^i t-1}(\, y_0^i - \bar{y}_0^i \,)\right\}$$

Although this expression is not reducible to a simpler form, simulations show that the first differences (i.e.: growth rates) are a nonlinear deterministic function of time and approach the exogenous growth rate γ^i asymptotically. Therefore, results from an equation in levels are unaffected by a switch to a log-linear approximation.

Table 1 [a]
Test for Per-Capita Income Growth Stationarity

State	DF t-test	DF T(r-1)	ADF t-test	ADF T(r-1)
Alabama	-12.56	-169.23	-14.40	-184.63
Arizona	-15.83	-210.59	-18.78	-173.40
Arkansas	-17.69	-231.12	-24.22	-304.68
California	-15.78	-210.23	-21.38	-205.74
Colorado	-17.21	-225.19	-24.59	-258.91
Connecticut	-13.34	-179.16	-10.24	-127.75
Delaware	-15.17	-204.43	-16.12	-192.10
Florida	-17.20	-225.59	-17.13	-154.09
Georgia	-13.52	-182.17	-15.25	-180.23
Idaho	-12.75	-172.31	-16.93	-217.20
Illinois	-13.40	-181.01	-13.05	-169.11
Indiana	-11.15	-147.53	-13.87	-178.80
Iowa	-12.29	-166.08	-15.86	-210.27
Kansas	-13.37	-180.24	-14.89	-191.16
Kentucky	-13.75	-181.85	-17.01	-217.62
Louisiana	-13.20	-178.01	-12.69	-162.65
Maine	-10.50	-136.96	-11.30	-141.36
Maryland	-14.01	-187.52	-12.95	-148.55
Massachusetts	-12.84	-173.87	-9.47	-118.87
Michigan	-11.82	-159.01	-13.06	-168.07
Minnesota	-13.08	-176.56	-16.49	-207.36
Mississippi	-19.50	-246.60	-19.63	-236.51
Missouri	-13.51	-183.17	-10.78	-142.64
Montana	-16.21	-216.05	-26.32	-337.33
Nebraska	-12.69	-170.40	-14.32	-189.59
Nevada	-16.70	-220.55	-16.68	-156.49
New Hampshire	-12.84	-173.46	-10.47	-129.93
New Jersey	-14.97	-200.98	-12.51	-156.24
New Mexico	-14.83	-197.25	-28.32	-311.22
New York	-19.35	-245.84	-14.54	-172.59
North Carolina	-13.41	-180.73	-13.57	-177.01
North Dakota	-13.38	-181.08	-15.19	-204.06
Ohio	-11.93	-159.59	-13.46	-171.17
Oklahoma	-15.69	-209.94	-18.56	-226.30
Oregon	-13.88	-187.72	-18.14	-219.09
Pennsylvania	-12.86	-173.72	-14.15	-184.56
Rhode Island	-11.91	-160.39	-11.60	-151.28
South Carolina	-13.98	-184.43	-17.50	-218.00
South Dakota	-11.85	-159.40	-21.75	-277.53
Tennessee	-12.73	-171.50	-15.69	-195.72
Texas	-15.29	-203.79	-12.16	-131.02
Utah	-16.33	-215.24	-31.74	-331.62
Vermont	-12.16	-161.81	-10.57	-130.03
Virginia	-14.72	-197.75	-11.90	-141.30
Washington	-15.88	-212.11	-14.01	-162.04
West Virginia	-15.96	-213.27	-19.10	-246.01
Wisconsin	-12.88	-171.87	-15.13	-189.69
Wyoming	-18.49	-219.64	-18.99	-213.76
United States	-12.82	-130.18	-16.77	-162.65

a. State per-capita income is a quarterly series running from 1948 to 1996.
US productivity (GDP / employee hour) is an annual series running from 1890 to 1997, with correction for two structural breaks in 1934 and in 1974.
Critical Value for the DF and ADF t-test at a 5% significance level: -2.89.
Critical Value for the DF and ADF T(rho-1) test at a 5% significance level: -13.85 .

Table 2 [a]

Test for the Presence of Trend in the First Differences of Per-Capita Incomes

	State	(a) Linear		(b) Quadratic				(c) Hyperbola	
		Trend	t-statistic	Trend	t-statistic	Trend^2	t-statistic	1/Trend	t-statistic
1	Alabama	-6.28E-08	-0.039	-3.37E-07	-0.038	1.37E-09	0.036	0.001241	0.164
2	Arizona	-1.45E-08	-0.010	-5.39E-07	-0.061	2.63E-09	0.065	0.002334	0.323
3	Arkansas	-6.19E-07	-0.348	-2.80E-06	-0.242	1.08E-08	0.211	0.006376	0.574
4	California	-2.09E-07	-0.167	6.31E-07	0.098	-4.22E-09	-0.147	0.001076	0.201
5	Colorado	3.42E-07	0.206	3.25E-06	0.343	-1.46E-08	-0.352	-0.001875	-0.210
6	Connecticut	-2.03E-07	-0.133	-9.07E-07	-0.116	3.52E-09	0.101	0.002964	0.421
7	Delaware	-2.64E-07	-0.158	-4.65E-07	-0.055	1.00E-09	0.027	0.002324	0.310
8	Florida	-3.09E-07	-0.204	-3.76E-06	-0.492	1.73E-08	0.459	0.003901	0.769
9	Georgia	-2.52E-07	-0.182	-1.36E-06	-0.185	5.64E-09	0.170	0.002787	0.565
10	Idaho	-7.65E-07	-0.342	-4.09E-06	-0.331	1.69E-08	0.299	0.006478	0.712
11	Illinois	-7.95E-08	-0.063	1.90E-07	0.029	-1.35E-09	-0.045	0.000552	0.106
12	Indiana	-1.44E-07	-0.084	-1.22E-06	-0.122	5.37E-09	0.120	0.002356	0.272
13	Iowa	2.05E-08	0.011	4.37E-06	0.348	-2.13E-08	-0.362	-0.002582	-0.251
14	Kansas	6.13E-07	0.388	8.32E-06	0.845	-3.73E-08	-0.854	-0.008155	-0.911
15	Kentucky	-6.09E-07	-0.380	-2.94E-06	-0.304	1.16E-08	0.275	0.006249	0.689
16	Louisiana	-2.61E-07	-0.174	-1.86E-06	-0.270	8.04E-09	0.269	0.002574	0.458
17	Maine	-3.03E-07	-0.219	-1.13E-06	-0.145	4.17E-09	0.117	0.002403	0.359
18	Maryland	-2.11E-07	-0.144	-1.10E-06	-0.138	4.41E-09	0.128	0.002945	0.396
19	Massachusetts	-8.52E-08	-0.065	-3.98E-07	-0.060	1.56E-09	0.052	0.001450	0.250
20	Michigan	5.80E-07	0.288	1.67E-06	0.148	-5.47E-09	-0.107	-0.003732	-0.376
21	Minnesota	-6.38E-07	-0.577	-1.99E-06	-0.283	6.85E-09	0.199	0.004709	1.047
22	Mississippi	-7.39E-07	-0.274	-5.94E-06	-0.419	2.63E-08	0.432	0.008067	0.708
23	Missouri	-5.30E-07	-0.478	-2.49E-06	-0.367	9.73E-09	0.310	0.005613	0.961
24	Montana	7.99E-07	0.321	6.87E-06	0.511	-3.02E-08	-0.467	-0.006953	-0.772
25	Nebraska	2.17E-07	0.097	5.56E-06	0.463	-2.63E-08	-0.506	-0.003497	-0.318
26	Nevada	-2.49E-07	-0.129	-1.28E-06	-0.134	5.13E-09	0.115	0.003878	0.504
27	New Hampshire	9.28E-08	0.077	-5.02E-07	-0.078	2.99E-09	0.096	0.000102	0.027
28	New Jersey	-3.52E-08	-0.026	1.12E-06	0.176	-5.82E-09	-0.198	-0.000012	-0.002
29	New Mexico	7.72E-08	0.064	-5.83E-07	-0.095	3.29E-09	0.120	0.001140	0.202
30	New York	1.32E-07	0.090	2.47E-06	0.381	-1.18E-08	-0.375	-0.001924	-0.463
31	North Carolina	3.58E-07	0.294	3.67E-06	0.485	-1.60E-08	-0.462	-0.003830	-0.590
32	North Dakota	9.25E-09	0.002	7.39E-06	0.270	-3.69E-08	-0.280	-0.004383	-0.251
33	Ohio	1.77E-07	0.115	6.97E-07	0.089	-2.61E-09	-0.075	-0.000624	-0.097
34	Oklahoma	-5.20E-07	-0.298	-1.15E-06	-0.128	3.15E-09	0.080	0.003215	0.432
35	Oregon	-2.89E-07	-0.182	-9.38E-07	-0.110	3.24E-09	0.087	0.002663	0.354
36	Pennsylvania	-9.39E-08	-0.067	-2.88E-07	-0.043	9.83E-10	0.034	0.001197	0.264
37	Rhode Island	-1.68E-07	-0.115	-1.10E-06	-0.162	4.65E-09	0.145	0.002456	0.419
38	South Carolina	-2.79E-07	-0.137	-2.51E-06	-0.218	1.12E-08	0.221	0.005191	0.488
39	South Dakota	-1.85E-07	-0.053	3.92E-06	0.219	-2.05E-08	-0.253	-0.000937	-0.077
40	Tennessee	1.53E-08	0.014	-5.14E-07	-0.077	2.66E-09	0.086	0.000229	0.045
41	Texas	-5.08E-07	-0.374	-2.62E-06	-0.409	1.07E-08	0.371	0.004591	0.904
42	Utah	1.42E-07	0.092	1.32E-06	0.165	-5.92E-09	-0.171	-0.000267	-0.039
43	Vermont	-2.23E-07	-0.187	-1.38E-06	-0.241	5.87E-09	0.214	0.002613	0.722
44	Virginia	-7.73E-09	-0.007	4.84E-08	0.008	-2.82E-10	-0.010	0.001142	0.217
45	Washington	-2.95E-07	-0.248	7.07E-08	0.010	-1.84E-09	-0.056	0.001873	0.446
46	West Virginia	-6.63E-07	-0.262	-5.39E-06	-0.471	2.39E-08	0.505	0.007548	0.854
47	Wisconsin	7.45E-08	0.053	4.30E-07	0.058	-1.79E-09	-0.054	0.000366	0.059
48	Wyoming	5.46E-07	0.269	4.55E-06	0.525	-2.01E-08	-0.517	-0.004566	-0.660
	United States	3.61E-06	0.067	-8.39E-05	-0.343	8.03E-07	0.367	0.013836	0.240

a. State per-capita income is a cyclically adjusted quarterly series running from 1949:1 to 1996:1.
US productivity (GDP / employee hour) is an annual cyclically adjusted series running from 1893 to 1994, and is also adjusted for two structural breaks in 1934 and in 1974.

Table 3

Panel Trend Regression:

Test for Same Growth Path

	Alabama coefficient	Alabama coefficient	Colorado coefficient	Colorado coefficient
Constant	8.5116		8.980175633	
Growth		0.00639523		0.005506907
	Fixed effects Differences	Growth coefficient differences	Fixed effect differences	Growth coefficient differences
Alabama			-0.4685	0.000888
Arizona	0.4074	-0.001694	-0.0611	-0.000806
Arkansas	-0.0693	0.000066000**	-0.5379	0.000954
California	0.7243	-0.002185	0.2557	-0.001296
Colorado	0.4685	-0.000888		
Connecticut	0.7230	-0.001000	0.2545	-0.00011200**
Delaware	0.7724	-0.002499	0.3038	-0.001611
Florida	0.3148	-0.000504	-0.1538	0.000384
Georgia	0.1217	0.003116	-0.3468	0.001200
Idaho	0.3748	-0.001967	-0.0938	-0.001079
Illinois	0.7035	-0.002136	0.2350	-0.001248
Indiana	0.5116	-0.002036	0.0430	-0.001148
Iowa	0.4691	-0.001844	0.000523**	-0.000956
Kansas	0.4388	-0.001298	-0.0298	-0.000410
Kentucky	0.1102	-0.000616	-0.3584	0.000272
Louisiana	0.1621	-0.000869	-0.3064	0.000020000**
Maine	0.2605	-0.001194	-0.2081	-0.000306
Maryland	0.5586	-0.000938	0.0873	-0.00005000**
Massachusetts	0.5338	-0.000779	0.0653	0.000109000**
Michigan	0.6137	-0.002192	0.1451	-0.001304
Minnesota	0.4110	-0.000729	-0.0575	0.000160
Mississippi	-0.1882	0.000166	-0.6567	0.001054
Missouri	0.4546	-0.001671	-0.013974**	-0.000782
Montana	0.5185	-0.003086	0.0499	-0.002198
Nebraska	0.4384	-0.001500	-0.0301	-0.000611
Nevada	0.7765	-0.002670	0.3079	-0.001781
New Hampshire	0.3619	-0.00008100**	-0.1067	0.000807
New Jersey	0.6496	-0.000912	0.1810	-0.00002400**
New Mexico	0.2855	-0.001813	-0.1831	-0.000924
New York	0.6887	-0.001872	0.2202	-0.000984
North Carolina	0.1027	0.000089000**	-0.3658	0.000978
North Dakota	0.2815	-0.001344	-0.1871	-0.000456
Ohio	0.5797	-0.002319	0.1112	-0.001431
Oklahoma	0.2536	-0.001035	-0.2150	-0.000147
Oregon	0.5576	-0.002391	0.0891	-0.001503
Pennsylvania	0.4985	-0.001684	0.0300	-0.000795
Rhode Island	0.4748	-0.001580	0.006222**	-0.000691
South Carolina	0.007100**	0.000041000**	-0.4614	0.000930
South Dakota	0.2658	-0.001362	-0.2027	-0.000474
Tennessee	0.0724	0.000122000**	-0.3961	0.001010
Texas	0.3508	-0.000851	-0.1177	0.00003700**
Utah	0.3886	-0.002297	-0.0800	-0.001408
Vermont	0.2424	-0.000538	-0.2262	0.000351
Virginia	0.2778	0.000169	-0.1907	0.001058
Washington	0.5836	-0.001866	0.1151	-0.000978
West Virginia	0.1507	-0.001611	-0.3179	-0.000723
Wisconsin	0.4984	-0.001807	0.0299	-0.000919
Wyoming	0.5817	-0.002203	0.1132	-0.001315

** Denotes not statistically significant at 5% level.
All other coefficients are significant at the 5% level.

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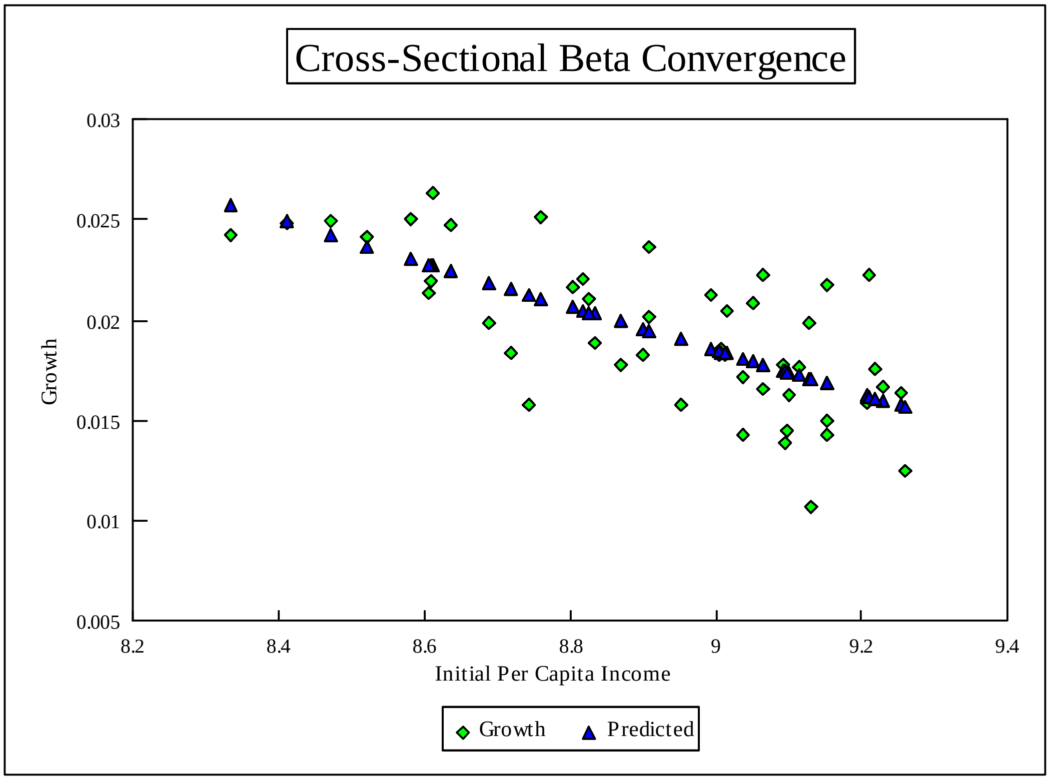
Figure 1
Beta Convergence Estimated across the U.S. States



Estimated Equation:

$$g_i = 0.1162 - 0.0109\, y_0^i$$

$$with: \beta = -0.0155$$

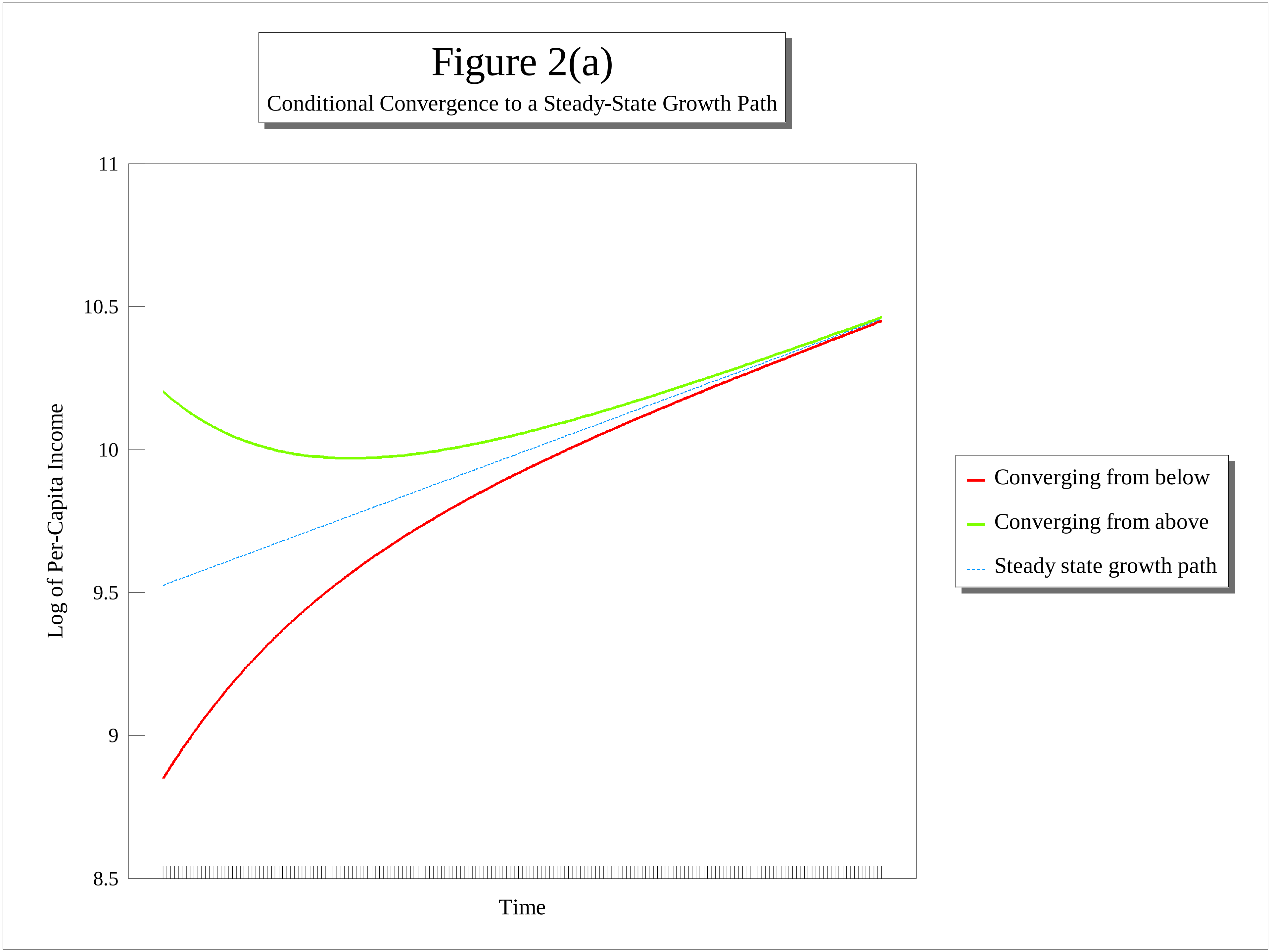


Figure 2(a)
Conditional Convergence to a Steady-State Growth Path
11
10.5
10
9.5
9
8.5
Log of Per-Capita Income
Time
Converging from below
Converging from above
Steady state growth path

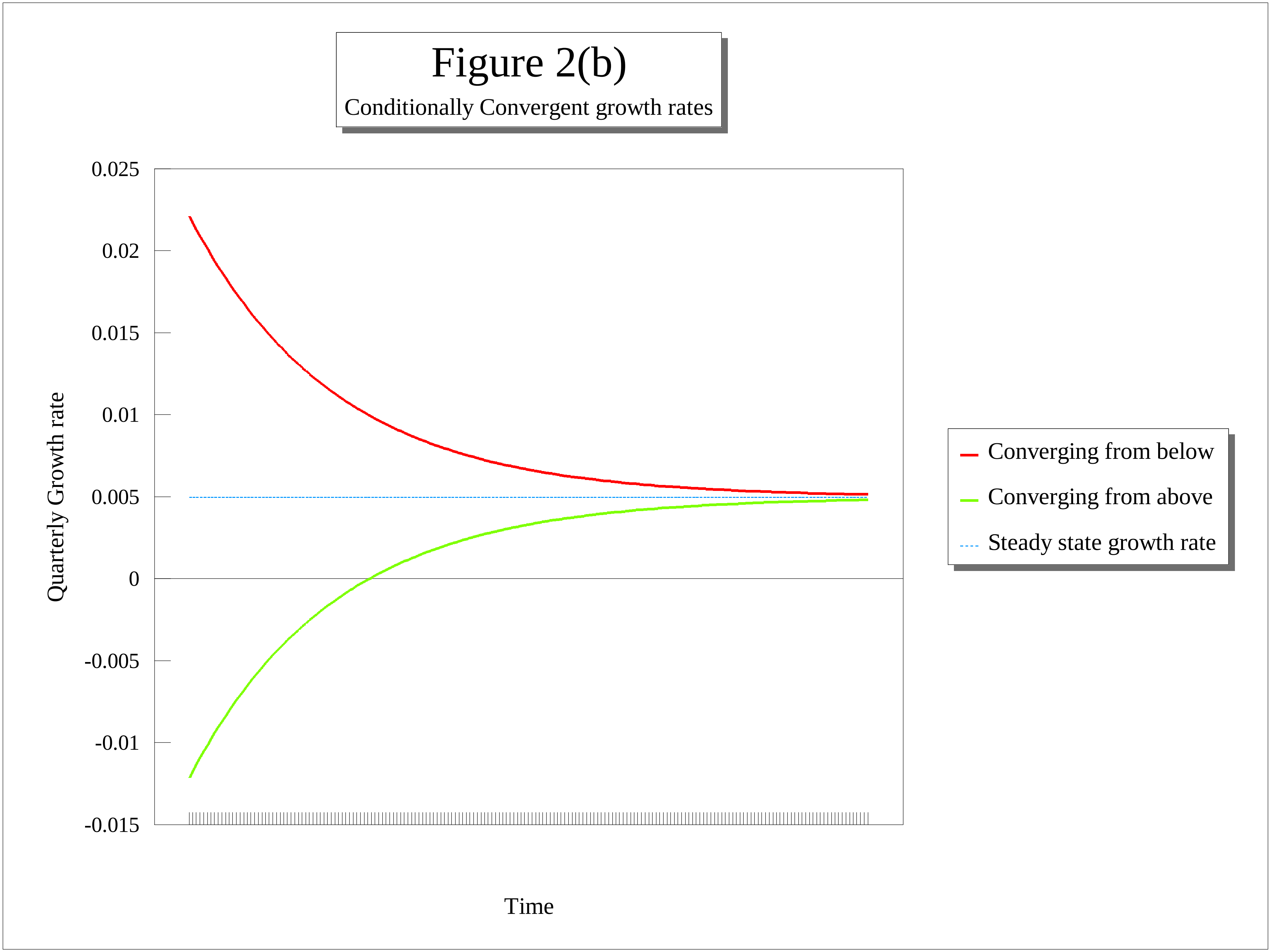


Figure 2(b)
Conditionally Convergent growth rates
0.025
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
Quarterly Growth rate
Time
Converging from below
Converging from above
Steady state growth rate