Technological Convergence Among U.S. Regions and States

(Short running title: Technological Convergence)

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Abstract

This paper employs unit root tests that allow for two endogenously determined structural breaks to study whether or not invention activities are converging across U.S. regions/states. Using U.S. patent data from 1929 to 1997, we find technological β-convergence in six of the nine Census regions, in 11 of the 14 leading states and in 28 of the 34 lagging states. Stochastic convergence, on the other hand, is found in three regions, in four leading states and in 17 lagging states. Carlino and Mills (1993) point out that both β- and stochastic convergence are necessary conditions for convergence. Putting these results together, we find convergence (both β- and stochastic) in invention activities in three regions, in three leading states and in 16 lagging states.

Keywords: Patent; U.S. Regions and States; β-Convergence; Stochastic Convergence; Unit Root Test

JEL Classification: O31; O18; C32

1. INTRODUCTION AND BACKGROUND

Most time series studies on innovation deal with aggregate patenting activities. Some papers attribute the recent surge in patenting to a widening set of technological opportunities and to changes in the management of research (see e.g., Kortum and Lerner (1998)) while others ascribe the jump to a series of changes in domestic patent policy starting in 1980 (see. e.g., Hall and Ziedonis (2001)).[1] While these studies explain (aggregate) patent behavior over time, there is much to be gained by examining patent behavior both across time and space. This is because patent specializations differ across space and patenting are not distributed uniformly—they tend to cluster spatially.

The clustering tendency of invention-related activities is well documented. One set of evidence is based on an extensive database of commercial innovations in 1982 (see e.g., Feldman (1994)); another set of evidence uses patent citation data (see e.g., Jaffe *et al.* (1993)). One implication of the clustering tendency of inventions is that regions with initially high patent counts will experience faster growth in patents as these regions have relatively high concentrations of supporting institutions that facilitate additional inventions; and, regions with initially low patent counts can expect to remain laggards in the invention race. Evidence, however, suggests otherwise; lagging regions appear to experience technological catch-up (see e.g., Co (2002), Johnson and Brown (2002), Varga (1999), Sokoloff (1988)).

Figure 1a plots the log relative patent per capita (defined as log of patent per capita in area i to patent per capita in the U.S. at time t) for the four patent leading

[1] The former is referred to as the fertile technology hypothesis and the latter is referred to as the friendly court hypothesis.

regions from 1929 to 1997. Figure 1b plots the log relative patent per capita for the five lagging regions.[2] Two patterns are evident: first, patent per capita in two leading regions (Middle Atlantic and East North Central) have declined over time; second, initially lagging regions have experienced invention catch-up.[3] While these plots are suggestive of invention catch-up and convergence, we use time series techniques to formally test whether or not invention activities across U.S. Census regions (and states) are converging. This paper is partly motivated by Aghion and Howitt's (1998) challenge to test the consistency of the predictions of Schumpeterian growth theory with empirical data. Using a two-economy framework, they extend the basic Schumpeterian growth model by incorporating between-economy knowledge spillover, in addition to within-economy spillover. In other words, the basic Schumpeterian growth model predicts non-convergence of per capita income because of within-economy agglomeration economies. The addition of between-economy knowledge spillover permits conditional per capita income convergence. We believe that one of the factors behind per capita income convergence across U.S. regions and states is the convergence of inventive activities in these areas.

Figures 1a and 1b near here

[2] For brevity, we refer to patent per 100,000 inhabitants as patent per capita. If a region's patent per capita is above (below) the average annual U.S. national rate in 1929-1935, it is considered a leading (lagging) region. We take the seven-year average to mitigate annual fluctuations in patenting. The average annual U.S. national rate is 34.89 per 100,000 inhabitants in 1929-1935.

[3] Suarez-Villa (2000) refers to this process as regional inversion.

We adopt Carlino and Mills's (1993) notion of convergence in our empirical tests. That is, convergence requires that economies with per capita patents above their compensating differential should exhibit slower patent growth than economies whose patent per capita are initially below their compensating differential (β-convergence) and shocks to relative patent per capita are temporary (stochastic convergence).[4]

Using U.S. patent data from 1929 to 1997, we find evidence consistent with β-convergence in invention activities in six of the nine Census regions, in 11 of the 14 leading states and in 28 of the 34 lagging states. Stochastic convergence, on the other hand, is found in three regions, in four of the 14 leading states and in 17 of the 34 lagging states. Carlino and Mills (1993) point out that both β- and stochastic convergence are necessary conditions for convergence. Putting these results together, we find convergence (both β- and stochastic) in invention activities in three regions, in three of the 14 leading states and in 16 of the 34 lagging states. Although the evidence is not

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[4] Per capita income convergence was initially tackled using cross-section data (see e.g., Barro and Sala-i-Martin (1992)). Convergence (β-convergence) in this context is defined as a negative relation between the initial levels of per capita income and the growth rates of per capita income. This approach has received much criticism. One criticism is its use of only the initial and terminal values (in calculating growth rates) of the data series under investigation. This led to the use of time series data, which uses a stochastic definition of convergence. In this approach, convergence is achieved when income disparities between economies follow a zero mean stationary process or shocks to relative per capita income are temporary. Results using cross-section and time series data are often contradictory. This led Carlino and Mills (1993) to develop

overwhelming, some regions with patent per capita above (below) their compensating differential do exhibit slower (faster) patent growth; and in some regions, relative patent per capita tend to return to their deterministic trends after a shock.

Multiple forces operate in the different regions; hence, it is not surprising that we find mixed results. For example, "technological" shocks can emanate nationally (e.g., changes in U.S. patent policy starting in 1980) and/or from within the regions themselves (e.g., creation of a research park). Since regional patent specialization differs (see e.g., Co (2002)), even shocks that originate nationally are expected to have differential impacts on regions. For example, changes in U.S. patent policy may have a permanent impact on regions specializing in biotechnology but have a temporary impact on regions specializing in farm machinery patents.

It should be pointed out that we do not aim to provide a comprehensive explanation to the temporal behavior of patent activities in all regions, rather our objective is more modest: We provide initial formal evidence that the temporal behavior of patenting activities over time vary across regions and this needs to be taken into account in innovation studies. We also aim to put in perspective the recent surge in patent activities. For the most part, structural breaks do not all occur after changes in U.S. patent policy; more than half of the (second) structural breaks are identified prior to 1980.

The rest of the paper proceeds as follows. In Section 2, we provide the theoretical basis for conducting convergence tests using patent data; Section 3 contains a

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a test that incorporates these two notions of convergence. They point out that both β- and stochastic convergence are necessary conditions for convergence.

detailed discussion of the data and empirical method used. The results are presented and analyzed in section 4. Finally, section 5 provides some policy implications and concluding comments.

2. THEORETICAL FRAMEWORK

Knowledge does not play a central role in the neoclassical growth model because it is assumed to flow instantly within and between regions (see Caniëls (2000) for a review). Accumulation of capital is the mechanism that drives convergence in this model. This has the following implication: Technology gaps do not exist between regions; that is, one should find unequivocal evidence in favor of convergence when convergence tests are performed on say, patent data.

Regions' abilities to adopt new knowledge is assumed to differ in endogenous growth models (see e.g., Romer (1990) and Grossman and Helpman (1991)), that is, knowledge diffusion is imperfect; hence, regional per capita income do not converge. Initial differences in knowledge are further reinforced by within economy temporal knowledge diffusion. Institutional arrangements and geography also differ across regions (see e.g., Gallup *et al.* (1999)), hence even if knowledge diffuses, per capita income need not converge. These have the following implication: Technology gaps between regions persist; one should find unequivocal evidence in favor of non-convergence when convergence tests are performed on patent data, for example.[5]

[5] It should however be pointed out that policy can impact long-run growth rates in endogenous growth models. This suggests that technology oriented policies such as research and development (R&D) subsidies can be put in place to close technology gaps among regions thereby leading to per capita income convergence.

Aghion and Howitt (1998) extend the basic Schumpeterian model by incorporating between-economy knowledge spillover. In particular, they define a region's knowledge, *A*, at time *t+1* as follows:

$$A_{t+1} = F(A_t, A^*_\tau), \qquad (1)$$

where A_t is within-economy (or intra-region or inter-temporal) spillover and A^*_τ is between-economy (or inter-region) spillover. $A^*_\tau = e^{g\tau}$, where g is the average growth rate of all regions and τ denotes the period when the next invention occurs at time τ and $(\tau + d\tau)$.

The effect of agglomeration economies appears in the first component of F(.,.). Knowledge at time *t+1* builds on knowledge at time *t*, hence those that start with "a lot of" knowledge will have "a lot more" knowledge in the next period, *ceteris paribus*. This is because these locations have relatively high concentrations of supporting institutions that facilitate further knowledge creation (see e.g., Audretsch and Feldman (1996) and Feldman (1994)). However, agglomeration forces do not work forever. This is because congestion costs, such as higher wages or rents, can overwhelm benefits from agglomeration (see e.g., Fujita and Thisse (1996)). Thus, one factor that may lead to inter-region knowledge spillover (the second component of F(.,.)) is intra-region congestion. It should be pointed out though that congestion is not a necessary condition for spillover: lagging regions can benefit from knowledge created in leading regions even without congestion. Our point is that agglomeration forces do not work forever; agglomerations may form in new areas. This sets the stage for possible catch-up by invention lagging areas. That is, regions with current knowledge above (below) the average will experience slower (faster) growth in the number of inventions; this leads to convergence (β-convergence) in inventive activities.

The latter feature of the model can be extended naturally to allow for knowledge diffusion to be a function of distance.[6] In other words, not only do lagging regions benefit from knowledge spillover from leading regions, those closest to the leading regions benefit more. This argument is consistent with Markusen *et al.*'s (1986) finding that "…there is much potentially mobile employment in high tech sectors…[However], it is relatively short distance dispersal." (p. 172)

Besides geographical distance, whether a lagging region has the requisite capability in place to build on knowledge developed in leading regions also determines the extent of knowledge spillover (see e.g., Caniëls (2000)). For example, most Northern Pacific and Mountain region states experienced extraordinary growth in total patent grants between 1929-1935 and 1991-1997; this is perhaps because of their proximity to California.[7] However, not all states experienced significant growth; this is because states' abilities to take advantage of knowledge developed in California vary.[8]

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[6] As reviewed in Section 1, there is strong empirical evidence that knowledge diffusion is geographically mediated.

[7] As Smith (1999, p. 350) points out, "…interstate knowledge spillovers are contained within industries and that the geographic proximity of states is more important than technological similarity for transmitting knowledge spillovers."

[8] This is related to the argument put forth by Abramovitz (1986) that lagging regions need to have the necessary "social capabilities" (e.g., a well-educated workforce) to catch-up.

Aghion and Howitt's (1998) model can be extended to include these two features: First, discovery of new ideas in existing fields becomes harder over time hence research and development (R&D) investment in existing fields will not always increase knowledge in future periods (see e.g., Kortum (1997)). In the extreme, no new ideas in the field will come about. This suggests that regions need to attract inventive activities related to emerging industries for regional knowledge to continually expand. In other words, leading regions unable to reinvent themselves lose their leads.[9] Those able to attract activities related to emerging technological fields maintain or even enhance their leads. This reinvention starts a new cycle whereby benefits from the agglomeration of these new (more technologically advanced) activities outweigh agglomeration benefits from extant activities and/or the cost of congestion. Second, in addition to knowledge diffusion as the mechanism for catch-up, we assume that regions experience "technological" shocks. These shocks may be policy induced such as the creation of the Court of Appeals of the Federal Circuit (CAFC) in 1982;[10] or, they may be events such as disruptions caused by World War II. This feature allows us to extend Aghion and Howitt's (1998) notion of convergence (β-convergence) to include stochastic convergence. If the impact of a shock to log relative patent per capita dissipates over time, then relative patent per capita tend to return to its deterministic trend. That is, stochastic convergence is found.

[9] This is another reason why regions with patent per capita above their compensating differential exhibit slower patent growth. Co (2002) provides some examples.

[10] It should be pointed out that policy induced shocks may also emanate from within the region/state (e.g., the creation of a research park in state *i*).

This section has put forth arguments to support the empirics (β- and stochastic convergence tests) we perform in the next section. Endogenous growth theory predicts non-convergence; however, as we point out above, a finding of convergence is not inconsistent with endogenous growth theory when both inter-region spillover and "technology" shocks are taken into account.

3. DATA AND EMPIRICAL METHOD

3a. Data

The patent data employed are utility patent counts from 1929 to 1997.[11] The U.S. Patent and Trademark Office (USPTO) defines utility patents as patents "issued for the invention of a new and useful process, machine, manufacture, or composition of matter, or a new and useful improvement thereof…." Patents are granted to inventors (who can assign or license the patent) and the data are tabulated using the reported state (aggregated into Census regions) residence of the inventors. In cases where there are multiple inventors, the residence of the first named inventor is used by the USPTO to allocate each patent's geographic origin.

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[11] Patent counts prior to 1963 include utility, design and plant patents. Data from 1929 to 1962 are from the U.S. Patent and Trademark Office, *Technology Assessment and Forecast, Seventh Report*. U.S. Department of Commerce, Arlington, VA: U.S. Dept. of Commerce, Patent and Trademark Office, Office of Technology Assessment and Forecast, March 1977. Data from 1963 to 1997 are from the U.S. Patent and Trademark Office, Information Product Division, *Patenting Trends in the U.S., 1998, State/Country Report- All Years, 1963-1998.* CD-Rom issued July 2000.

The patent count data are adjusted using Census region and state population. Total patents ideally need to be adjusted by the number of R&D scientists and engineers in the region (state); however, the geographical distribution of the number of doctoral scientists and engineers by state is not available annually and as far as we know the data series only started in the late 1970s. The use of patent per 100,000 inhabitants is appropriate. For example, the correlations between state patent per 1,000 R&D scientist and engineer and state patent per 100,000 inhabitants for periods when data are available are around 0.70.

The first two columns of Table 1 contain the growth rates for total patents and patent per capita across U.S. regions and states, respectively. The third and fourth columns contain patent per capita values in the initial and terminal periods.[12] For the most part, regions (states) whose patent per capita is higher than the annual average U.S. national rate in 1929-1935 experienced either slower or negative growth in patents as compared to lagging regions (states). For example, the Middle Atlantic and East North Central regions experienced negative growth of about 30% and 22% respectively in total patents and more than 50% drop in patent per capita. All lagging regions (except West North Central) experienced significant growth in total patents and patent per capita increased in these regions as well. These patterns are also evident in the state data.

Table 1 near here

[12] To mitigate the effect of annual fluctuations in patenting, we use a seven-year initial (1929-1935) and terminal (1991-1997) period to calculate the growth rates.

High wages and rents may have contributed to the negative growth in patenting experienced by the Middle Atlantic and East North Central regions.[13] Breakthroughs in well-established technologies have become harder over time hence leading regions (e.g., Middle Atlantic region with negative growth in total patent counts) unable to reinvent themselves lose their leads; regions (e.g., the Pacific region with growth of about 184% in total patent counts) able to attract research activities in emerging industries either maintain or enhance their leads.[14] Lagging states could benefit from spillovers from leading neighboring states with significant inventive activities in emerging new industries. For example, proximity to California may be one reason for the extraordinary growth experienced by most states in the North Pacific and Mountain regions. Another mechanism for catch-up is the adoption of policies conducive to the formation and growth of R&D related activities in emerging technologies. This is exemplified by North Carolina's early commitment to technology programs; for example, it created an

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[13] For example, using data from the Bureau of Economic Analysis, between 1969 (the earliest year for which this data is available) and 1997, the average wage per job in the Middle Atlantic region was higher than the U.S. average wage per job in every year. The differential ranged between 5% (in 1981) and 17% (in 1996). Although average wage in the East North Central region has been below the U.S. average since 1987, between 1969 and 1986, wages are 5% higher in the region. Average wage in New England (Pacific) is 9% lower (3% higher) than the U.S. average.

[14] For example, using patent data from 1963 to 1997, Co (2002) presents evidence that states in New England and the Pacific region experienced significant changes in their patent specialization between 1963-1969 and 1991-1997 while state patent specialization in the Middle Atlantic and the East North Central regions did not change drastically.

Industrial Extension Service as early as 1952, followed by the initial development phase of the Research Triangle Park in 1953 (see Coburn and Berglund (1995)). This no doubt contributed to the state's total and per capita patent growth.

Figures 1a-1b and Table 1 are suggestive of catch-up and convergence. To marshall further evidence consistent with convergence, we employ unit root testing procedures. The empirical methodology is discussed in the next section.

3b. Empirical Methods

Following Carlino and Mills (1993), we use the following equation to test for convergence using time series data:

$$RP_{it} = RP_i^e + u_{it}, \qquad (2)$$

where RP_{it} is the log of patent per capita in region (state) i to patent per capita in the U.S. at time t. This consists of two parts: a time-invariant equilibrium differential, RP_i^e and deviations from this equilibrium, u_{it}.[15]

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[15] As one referee points out, this approach although appropriate is not without limitations. For example, it does not account for the relationships among cross-sectional units. That is, "… estimating individual time series models—one for each state, say, to permit differences across Maine and Oklahoma (e.g., Carlino and Mills (1993))—leaves undetected the co-movements across states." Quah (1996, p. 147) Bernard and Durlauf (1995, 1996) provide an alternative time series approach that accounts for relationships among countries. In their formulation, convergence is found when the log of real per capita output differences between countries i and s is a mean zero stationary process. Since this approach analyzes pairwise differences in output, it has a nice feature in that all countries may not be converging but they are able to identify subgroups that are. Quah (1992) extends standard unit root test procedures to account for

The time-invariant differential could be attributed to permanent differences in area characteristics. That is, some areas will always be conducive to inventive activities more than others—knowledge creation activities are expected to thrive in certain areas but not in others. One factor that contributes to permanent differences in invention attractiveness across locations is resource endowments.[16] Endowment differences in turn shape the composition of production activities in these areas. A connection between invention and the diversity of economic activities has been established in the literature. For example, Jacobs (1969, p. 59) suggests that "… the greater the sheer number of and variety of division of labor, the greater the economy's inherent capacity for adding still more kinds of goods…" In other words, diversity in production is conducive to inventive activities. Hence, all else equal, a state with a more diverse production base would always invent more in equilibrium.[17]

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possible dependence in the cross-section dimension. He considers whether income differences between countries *i* and *s* (a benchmark country) is a mean stationary process. Quah (1992) finds non-convergence of per capita income using various countries as benchmarks.

[16] Another factor is locational amenities that tend to attract skilled workers or high-tech industries (see e.g., Davelaar and Nijkamp (1997) and Markusen *et al.* (1986)). Also see Gallup *et al.* (1999) who emphasize the role of geography in economic growth using cross-country data and Bloom *et al.* (2002) who point to geography as a contributing factor to the persistent differentials in total factor productivity across countries.

[17] Alfred Marshall makes a contrary observation. He observes that increased production specialization is conducive to greater inventive output. The evidence in favor of diversity though is quite compelling (see e.g., Feldman and Audretsch (1999)).

The term u_{it}, in equation (2) is assumed to be a stochastic process with a linear trend and drift,

$$u_{it} = v_o + \beta t + \varepsilon_{it}, \tag{3}$$

where v_o is the initial deviation from equilibrium and β is the deterministic rate of convergence. As Carlino and Mills point out, β-convergence implies that regions (states) with per capita patents above their compensating differential, $v_o > 0$, should exhibit slower patent growth, $\beta < 0$. Substituting equation (3) into (2) yields:

$$RP_{it} = RP_i^e + v_o + \beta t + \varepsilon_{it}. \tag{4}$$

Equation (4) can be rewritten as follows (suppressing region/state subscript):

$$RP_t = \mu + \beta t + \varepsilon_t, \tag{5}$$

where $\mu = RP_i^e + v_o$. Stochastic convergence is achieved if the series does not contain a unit root or is a (trend) stationary series; that is, shocks to log relative patent per capita are temporary.[18]

Past studies (see e.g., Lumsdaine and Papell (1997), Zivot and Andrews (1992) and Perron (1989)) have shown that it is possible that wrong inferences are reached about whether or not a data series is non-stationary if structural breaks are ignored and/or if an incorrect number of breaks are considered. Structural breaks in the patent per capita data can be attributed to shocks that are exogenous to a region and/or shocks that emanate from the region. There are several plausible reasons why one should incorporate structural breaks in the patent per capita data. First, the passage of the Bayh Dole Act in 1980 and the creation of the CAFC in 1982 are widely believed to have

[18] Also see Loewy and Papell (1996) and Carlino and Mills (1996).

created a pro-patent environment thereby changing patenting behavior.[19] Second, macroeconomic events such as disruptions caused by World War II may also be a source of a structural break in the time path of patenting. Third, technology oriented economic development policies became very popular in the late 1970s and early 1980s (see Coburn and Berglund (1995) and Bartik (1991)) and these initiatives may have also led to a structural break in the time path of patenting across regions and/or states. Fourth, states begun offering tax breaks, direct loans, loan guarantee programs, etc., in the 1950s. These economic development initiatives were complemented by substantial investments in higher education after World War II (see Suarez-Villa (2000)).

We consider the unit-root test developed by Lumsdaine and Papell (1997). The procedure allows for two distinct structural breaks in both the intercept and trend terms determined endogenously. The null and alternative hypotheses are given as follows:

$$H_0 : y_t = \mu_0 + y_{t-1} + \varepsilon_t$$

$$\begin{aligned} H_a : y_t &= \mu_1 D_{L1,t} + \mu_2 D_{L2,t} + \mu_3 D_{L3,t} \\ &\quad + \beta_1 D_{T1,t} + \beta_2 D_{T2,t} + \beta_3 D_{T3,t} + \varepsilon_t \end{aligned} \tag{6}$$

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[19] Congress passed the Bayh-Dole Act in 1980. Universities are able to retain the rights to inventions emanating from federally funded research with this law. This is believed to be one of the important contributory factors in the development of the biotechnology industry (see e.g., Evenson (2002) and Pisano (2002)). In 1982, the CAFC was created to hear patent cases. This regime change created a patent friendly environment and may be one reason for the significant increase in the number of patents taken out by firms in the semiconductor industry (see e.g, Hall and Ziedonis (2001)).

where y_t is any data series, $D_{L1,t}$, $D_{L2,t}$ and $D_{L3,t}$ are level dummy variables defined as follows:

$D_{L1,t}$ =1, if $0 < t < TB1$, zero otherwise;

$D_{L2,t}$ =1, if $TB1 \leq t \leq TB2$, zero otherwise;

$D_{L3,t}$ =1, if $t > TB2$, zero otherwise.

$D_{T1,t}$, $D_{T2,t}$ and $D_{T3,t}$ indicate shifts in the trend function defined as follows:

$D_{T1,t}$ = (t), if $0 < t < TB1$, zero otherwise;

$D_{T2,t}$ = ($t - TB1$), if $TB1 \leq t \leq TB2$, zero otherwise; and,

$D_{T3,t}$ = ($t - TB2$), if $t > TB2$, zero otherwise,

where t is time, μ_m and β_m are coefficients associated with the intercept and trend, respectively, for regime m (m=1,2,3), ε is a well-defined error term; and, $TB1$ and $TB2$ are defined as the first and second hypothesized break dates assumed to satisfy the following conditions:

$$\delta T \leq TB1,\; TB2 \leq (1-\delta)T \;\text{ and }\; |TB1 - TB2| \geq 2, \tag{7}$$

where T is the length of the data series and δ is a trimming parameter set at 0.05.

We test for the null hypothesis of a unit root against the alternative that the series is trend stationary with two distinct shifts in the intercept and deterministic trend. We employ the following regression to test for a unit root:

$$\begin{aligned}\Delta RP_t &= \mu_1 D_{L1,t} + \mu_2 D_{L2,t} + \mu_3 D_{L3,t} + \beta_1 D_{T1,t} + \beta_2 D_{T2,t} + \beta_3 D_{T3,t} \\ &\quad + \rho\, RP_{t-1} + \sum_{j=1}^{k} d_j \Delta RP_{t-j} + \varepsilon_t ,\end{aligned} \tag{8}$$

where ΔRP_t is the change in log relative patent per capita, ΔRP_{t-j} is the lagged change in the log relative patent per capita.[20] If ρ is insignificantly different from zero (ρ=0), then shocks to log relative patent per capita are permanent and have a unit root. On the other hand, if ρ is significantly less than zero (ρ<0), the unit root null hypothesis is rejected and shocks have temporary effects. The k extra regressors ΔRP_{t-j} are intended to eliminate possible nuisance-parameter dependencies in the asymptotic distributions of the test statistics caused by serial correlations in the error terms.

We first determine the optimal lag length for ΔRP_{t-j} by estimating equation (8) without the four dummy variables. We use a general to specific method starting with k_{max} equal to 8.[21] If the coefficient of the last included lag difference term is significant at the 10% level, select $k = k_{max}$. Otherwise, reduce the order of lags by one until the coefficient on the last included lag differenced term is statistically significant. After determining the optimal lag length, we use this lag length and estimate equation (8) for all combinations of two breaks. The selection of break dates TB1 and TB2 correspond to

[20] Equation (8) is Lumsdaine and Papell's (1997) model CC which is based on the sequential Dickey-Fuller test procedure of Zivot and Andrews (1992).

[21] Ng and Perron (1995) demonstrate that an overly parsimonious model can have large size distortions, while an over-parameterized model may have low power. But the size problem is more severe than power loss. They show that methods based on sequential tests have an advantage over both the Said and Dickey (1984) fixed-rule and information-based rules such as the Akaike information criterion and the Schwarz information criterion, because the former have less size distortions and have comparable power. The procedure adopted in this paper falls into this category of the general-to-specific sequential procedures.

the equation that yields the largest *t*-statistic (in absolute value) associated with the coefficient ρ.

As asymptotic critical values are often misleading in small samples, we compute the critical values for these test statistics using a bootstrap procedure. Five hundred pseudo-samples are generated from a random walk model with drift. For each pseudo-sample, the procedure outlined above is carried out. The largest t-statistic for ρ for each pseudo-sample is tabulated. We obtain the 1%, 5%, and 10% critical values from the empirical distribution of these *t*-statistics. These values are similar to those computed by Lumsdaine and Papell (1997), see their Table 3.

4. ANALYSIS OF RESULTS

Using patent data from 1929 to 1997, Tables 2 and 3 report the unit root test results for U.S. regions and states. The first column of both tables reports the region and state respectively. The second column contains the two break dates; these refer to the end of the first and second regimes, respectively. The third column contains the coefficient estimate (ρ) associated with the lagged level of the data series. The coefficient estimates for the dummy level shifts are reported in columns four (μ_1), five (μ_2) and six (μ_3). Columns seven (β_1), eight (β_2), and nine (β_3) report coefficient estimates for the trend slope coefficients. Finally, the last column reports the number of lagged difference terms included.

Tables 2 and 3 near here

For easy reference, we summarize the results in Table 4. Columns two to four indicate whether the evidence is consistent with β- convergence or divergence. If the coefficient estimates for the dummy level shifts and trend slope coefficients are statistically significant and are inversely related, then β- convergence is found. We adopt Tomljanovich and Vogelsang's (2002) approach and indicate with a *C* (*D*) those cases where both coefficient estimates are statistically significant with at least a 10% level of significance and are inversely (directly) related. Those with only one coefficient estimate statistically significant with at least a 10% level of significance are indicated with a *c* (*d*). Finally, β- convergence is also assumed to have occurred when an intercept term is very small and statistically insignificant. These cases are marked with an *E*. Column five indicates whether we find stochastic convergence with at least a 10% level of significance. This is evidenced by rejections of the unit root null hypothesis. The last column combines these results. There is strong evidence in favor of convergence when stochastic convergence is found and all three entries in columns two to four are *c*'s (or *C*'s or *E*'s). Moderate evidence in favor of convergence is found when the data converges stochastically and two entries in columns two to four are *c*'s (or *C*'s or *E*'s). There is weak evidence in favor of convergence when stochastic convergence is found and only one entry in the last three columns is a *c* (or *C* or *E*).

Summarizing the results from Table 4, we find β-convergence in invention activities in six of the nine Census regions, in 11 of the 14 leading states and in 28 of the 34 lagging states. That is, regions with patent per capita above (below) their compensating differential do exhibit slower (faster) patent growth.[22] Stochastic

[22] As we point out previously, if leading regions/states are not able to reinvent themselves, they can lose their leads, and/or exhibit slower patent growth. This is one potential explanation for our findings of β-convergence in leading regions/states. Regions need to constantly attract R&D activities related to emerging technological fields to keep their leads. As Suarez-Villa (2000, p.

convergence is found in three regions, in four of the 14 leading states and in 17 of the 34 lagging states. That is, the null hypothesis of unit root can be rejected in favor of the alternative hypothesis that log relative patent per capita can be characterized as a trend stationary process with two breaks in the intercept and trend function. Shocks have temporary effects in these areas.[23] Combining these results together, we conclude that part of the U.S. is converging. Evidence in favor of convergence is found in three regions: Middle Atlantic, West North Central and Pacific regions. Convergence is found in the following states: Massachusetts, Illinois, Michigan, Iowa, Kansas, Minnesota,

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175) points out, "[e]xisting knowledge [in an area] must… be supplemented with new ideas and creativity in order to come up with new discoveries and to sustain the pace of invention over the long term." Log relative patent per capita is also found to be diverging in some states, e.g., Connecticut prior to 1941; Kansas after 1972.

[23] The results indicate that shocks have permanent effects in over half of the regions and states. One limitation of the method we use is that if an incorrect number of breaks dates are included, wrong conclusions can be reached. For policy purposes, under rejection of the unit root null hypothesis is more problematic as an incorrect conclusion of a permanent impact (of a policy-induced shock) can lull policymakers into not taking actions to support state infrastructures for technology development, for example. Too few rejections (under rejection) of the unit root null hypothesis (conclude that shocks have permanent effects) will be reached if the true data generating process is a series containing only one break and two breaks are assumed in the estimation. To ensure robustness of our findings, we also performed unit root tests assuming one break in the intercept and trend. With the exception of Idaho, the results confirm those allowing for two breaks.

Missouri, Nebraska, North Dakota, Florida, Maryland, North Carolina, Virginia, West Virginia, Texas, Montana, Nevada, New Mexico, and Utah.

In section 2, we identified two main factors that can potentially contribute to technological convergence among U.S. regions and states: inter-region spillover and "technological" shocks. We also pointed out that knowledge spillover is a function of geographical distance (see e.g., Audretsch and Feldman (1996)) and the receiving regions' technological abilities (see e.g., Caniëls (2000)).[24] In particular, we suggested that proximity to California is one reason why most Northern Pacific and Mountain region states experienced extraordinary growth in total patents. To test this notion, we take a complementary approach to citation analysis. We ask whether lagging states' patent specialization rankings become more different (compared to California's) as their distance to California increases.[25] The second column of Table 5 contains each lagging

[24] Knowledge spillover is typically measured using patent citation data. However, patent citation data are currently available only for patents granted starting 1975 (see Hall *et al.* (2001)). Several papers have established that knowledge spillover is geographically mediated. For example, Jaffe *et al.* (1993) find that for patents issued in 1975 (1980), about 6-11% (10-14%) of the citations received up to 1989 are from the same state as the originating patent.

[25] Each state's capital is used to measure (as the crow flies) distance and the location quotient is used for patent specialization (see e.g., Co (2002) and Feldman (1994)). The location quotient measures the concentration of state *i*'s patent activity in industry *j* relative to the national level. The industry with the highest location quotient is state *i*'s top patent specialization. Patents granted beginning 1963 are also classified according to "industry of use". This USPTO data are used to tabulate each state's patent specialization between 1963 and 1997 (see Co (2002) for details).

states' distance from California; the remaining columns contain the Spearman (rank) correlation coefficients between California's patent specialization rankings in 1963-1969 and each lagging states' patent specialization rankings in several periods. A perfect positive Spearman correlation suggests that California and state *i*'s patent specialization ranking are exactly the same: suggestive of knowledge spillover from California. A perfect negative Spearman correlation means that patent specialization rankings between these two states are exactly opposite. Distance and the Spearman correlation coefficients are negatively related (the correlation falls between –0.31 and –0.48). This suggests that a state's patent specialization ranking becomes more different (from California's) when distance from California increases.

For the most part, the receiving regions' technological abilities are related to how much resources are devoted to R&D. We can only offer suggestive evidence that increased R&D may have contributed to β-convergence since state (or regional) level R&D data are not available prior to 1963 and convergence (when found) occurs mostly prior to 1963. Using total industry R&D data from NSF, there is indication that R&D performed by industry in the various lagging states increased significantly.[26] For example, the mean R&D (in current dollars) in leading states in 1963-1969 (1991-1997) is \$821 million (\$6,896 million) while the mean R&D in lagging states in 1963-1969 is

[26] Note that R&D data are available according to funding and performing sectors. These sectors are the federal government, industry, colleges and universities, non-federal government, federally funded R&D centers and other non-profit organizations. We consider only the first three major sources below.

$111 million ($1,162 million). In real terms, these translate to an increase of 87% and 134% for leading and lagging states, respectively.[27]

Using aggregate U.S. data, industry, on average, performed 70% of total R&D between 1953 and 1997 (1953 is the earliest year for which this data series is available); however, this sector funded only 45% of total R&D during the same period. The federal government, on average, conducted about 13% of total R&D and funded about 52% of total R&D; and, colleges and universities conducted about 9% of total R&D and funded about 1% of total R&D between 1953 and 1997 (see NSF (2001)).

The following characterizes the time paths of these series: First, the federal government funded the majority of total R&D up until 1980. Starting 1981, industry funded a larger portion of total R&D than the federal government and the latter's share continue to decline. By 1997, the federal government's share is about 31% (from 54% in 1953) while industry's share has risen to 64% (from 44% in 1953). The share of colleges and universities has been increasing; however, its share in total R&D funding is still comparatively low at 2% in 1997 (from about 1% in 1953). Second, the federal government's share in total R&D by performing sector increased between 1956 and 1971 (with minor declines) but has declined continuously since 1971; by 1997, the sector's share is at 8% (from 20% in 1953). Industry's share dropped from 74% to 66%

[27] These data pertain to R&D performed by industry and are available every year starting 1963 (see http://caspar.nsf.gov/nsf/srs/IndRD/start.htm). This data set has the widest temporal coverage at the state level; the breakdown for the other three sectors is not available for this length of time (it is available every two years since 1987) so we use aggregate information below.

between 1957 and 1972. With some minor dips, industry's share has been increasing since 1972; it was back to around 73% by 1997. The share of colleges and universities increased from 4% to 10% between 1957 and 1979; with some minor dips, this sector's share has been increasing since 1984 and is at 12% in 1997 (from about 5% in 1953).

Both the federal government (because it was the largest source of R&D funding) and industry (because most R&D was conducted by this sector) played significant roles in the catch-up (and invention growth) process before the 1980s. Although still important, the federal government's role has diminished since the 1980s. Colleges and universities have made increasing contribution since the late 1950s but their contribution is still very much overshadowed by industry's relative contribution. Industry's contribution to the catch-up (and invention growth) process since the 1980s is the most significant.[28]

The above conclusions need to be put in perspective as the relative importance of each sector varies by region/state. Using available data (see footnote 27), Table 6 contains the average share of each sector according to R&D performance. The federal government's share in the South Atlantic and East South Central regions is significantly higher than its share in the overall U.S. Industry's share in the Middle Atlantic and East North Central regions is significantly higher than its share in the U.S.; it is significantly lower in the South Atlantic, East South Central and Mountain regions. Finally, the share

[28] According to NSF (1999), state governments funded only 1% of total U.S. R&D in 1965 and about 1.18% in 1995. Although state governments' direct financial contributions to R&D is insignificant, they play an important role in the invention catch-up and growth process via their investments on education, workforce training, infrastructure, etc.

of colleges and universities in the South Atlantic, East and South Central regions is five percentage points above its share in the overall U.S. Although the entries in Table 6 only pertain to the most recent period, they suggest that the main contributor to invention catch-up may be businesses in some regions. In some regions, it may be the federal government. There are also variations within each region. For example, the federal government's share in Rhode Island is about 34%, in contrast to its share in New England of 5%. If these sectoral breakdowns do not change drastically in the future, we can surmise that industry will continue to be the main source of invention growth (hence main contributor to the catch-up process) in *most* states.

As previously mentioned, "technological" shocks may emanate nationally or from within a region/state. Table 6 summarizes the first and second break occurrences for easy reference. For the most part, the first break dates occur between 1945 and 1949. This is not surprising as these breaks are probably indicative of disruptions (and eventual recovery from these disruptions) caused by World War II. A number of states experienced structural (first and second) breaks in the mid-1950s to mid-1960s coincident with significant increases in federal and industry support to R&D and massive federal, state and local spending in physical and educational infrastructure after World War II (see e.g., Suarez-Villa (2000) and Nelson and Wright (1992)). Interestingly, the second break date for 15 states occurs after 1982, a consequence perhaps of changes in patent policy starting 1980 (assuming a two-year lag from R&D spending to patenting). The identified break dates indicate that although shocks can emanate from within regions/states, structural breaks in patent per capita, for the most part, appear to be coincident with "macroeconomic" shocks.[29] Shocks have temporary effects in states where stochastic convergence is found. That is, log relative patent per capita tend to return to its deterministic trend given a shock.

It is interesting to point out that although convergence (both β- and stochastic) is found for the Middle Atlantic region, we arrive at opposite conclusions for each of the three states in the region. In particular, this incongruence can be attributed to our findings on stochastic convergence. The effect of shocks is temporary at the regional level; the effects are permanent at the state level. This seeming incongruence between regional and state results, at first, may be attributed to aggregation problems; however, as we discuss below, the differential results are perhaps indicative of how knowledge diffuses and how agglomeration forces work. Combining the results in Table 3 with the declining time paths of the states' log relative patent per capita (not shown) suggest that shocks, i.e. negative shocks, have permanent effects. In other words, when states experience (negative) shocks and become unattractive locations for invention related activities, it is hard for them to recover from these shocks—shocks have permanent effects. While each state may have insufficient infrastructure to support new R&D activities, taken together, extant human and physical infrastructures in these states may

[29] The possibility that state *i* intensively engages in activities to attract invention-intensive activities during the same period is not ruled out. In fact, states have instituted technology-oriented economic development policies since the late 1970s; and we do not rule out the possibility that these also contributed to some of the structural breaks in log relative patent per capita identified in the 1980s.

be complementary hence the region as a whole does not lose its appeal. So, the effect of a negative shock at the regional level tends to dissipate over time.

Another interesting finding is that log relative patent per capita is found to be converging in the Pacific region; however, unit root tests at the state level suggest otherwise. This is again attributed to the results pertaining to stochastic convergence. The results in Table 3 combined with observations of increasing time paths of log relative patent per capita in these states (not shown) signify that shocks, positive shocks in this case, have permanent effects. This suggests that agglomeration forces are still at work at the state level. The regional result though is suggestive of the bounded nature of agglomerative forces.

5. POLICY IMPLICATIONS AND CONCLUDING COMMENTS

The purpose of this paper is to use time series techniques to formally test for both β-convergence and stochastic convergence in invention activities across U.S. Census regions and states. We employ unit root testing methodology that allows for two distinct endogenously determined structural breaks in the intercept and trend terms to investigate the issue of convergence. Our results lead us to conclude that part of the U.S. is converging. Evidence in favor of convergence (both β-convergence and stochastic convergence) is found in three regions and in 19 states (16 of which are lagging states).

Our mixed finding is not surprising as multiple forces operate in the different regions/states. For one, technological convergence depends on inter-region spillover. Both proximity to leading states and lagging states' technological abilities determine the extent of inter-region knowledge spillover. For the most part, the receiving regions' technological abilities are related to how much resources are devoted to R&D. We put forth evidence that both the federal government (because it was the largest source of R&D funding) and industry (because most R&D was conducted by this sector) played important roles in the catch-up (and invention growth) process before the 1980s. Although still important, the federal government's role has diminished since the 1980s. Colleges and universities have made increasing contribution since the late 1950s but their contribution is still very much overshadowed by industry's relative contribution.

Second, the identified "technological" break dates are coincident with macroeconomic events (e.g., disruptions and recovery from World War II, massive increases in federal and industry support to R&D and changes in U.S. patent policy in the 1980s). However, since regions/states have different specializations or characteristics, these have differential regional impacts. For example, we argue that changes in U.S. patent policy may have only temporary effects in areas specializing in farm machinery patents because appropriability benefits from these are far lower than those from biotechnology patents. Our results suggest that although these shocks may have contributed to invention catch-up, their impacts are temporary in 16 lagging states: log relative patent per capita in these states tend to return to their deterministic trends after a shock.

Although shocks of national origin seem to dominate, state level initiatives are not ruled out. In other words, we do not rule out "technological" shocks that emanate from within the regions/states themselves. However, identifying every state level initiative relating to technology since 1929 is a tedious (if not impossible) task which is beyond the scope of this paper. We leave this task as a challenge for the future.

REFERENCES

Abramovitz, M. (1986) Catching Up, Forging Ahead, and Falling Behind. *Journal of Economic History*, 46(2), 386-406.

Aghion, P. and P. Howitt (1998) *Endogenous Growth Theory*. Cambridge, MIT Press.

Audretsch, D. and M. Feldman (1996) R&D Spillovers and the Geography of Innovation and Production. *American Economic Review*, 86(3), 630-640.

Bartik, T. (1991) *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, Upjohn.

Barro, R. and X. Sala-i-Martin (1992) Convergence. *Journal of Political Economy*, 100(2), 223-251.

Bernard, A. and S. Durlauf (1996) Interpreting Tests of the Convergence Hypothesis. Journal of Econometrics, 71(1-2), 161-173.

Bernard, A. and S. Durlauf (1995) Convergence in International Output. Journal of Applied Econometrics, 10(2), 97-108.

Bloom, D., D. Canning and J. Sevilla (2002) Technological Diffusion, Conditional Convergence and Economic Growth. NBER Working Paper 8713, Cambridge: NBER.

Caniëls, M. (2000) *Knowledge Spillovers and Economic Growth*. Cheltenham, Edward Elgar.

Carlino, G. and L. Mills (1996) Are U.S. Regional Incomes Converging? Reply. *Journal of Monetary Economics*, 38(3), 599-601.

Carlino, G. and L. Mills (1993) Are U.S. Regional Incomes Converging? A Time Series Analysis. *Journal of Monetary Economics*, 32(2), 335-346.

Co, C. (2002) Evolution of the Geography of Innovation: Evidence from Patent Data. *Growth and Change*, 33(4), 393-423.

Coburn, C. and D. Berglund (1995) *Partnerships: A Compendium of State and Federal Cooperative Technology Programs*. Columbus, Battelle.

Davelaar E.J. and P. Nijkamp (1997) Spatial Dispersion of Technological Innovation: A Review. In C.S. Bertuglia, S. Lombardo and P. Nijkamp, (eds.), *Innovative Behaviour in Space and Time*. Berlin, Springer, 17-40.

Evenson, R. (2002) Agricultural Biotechnology, in B. Steil, D. Victor, R. Nelson (eds.) *Technological Innovation and Economic Performance*, Princeton University Press, Princeton.

Feldman, M. (1994) *The Geography of Innovation*. Dordrecht, Kluwer.

Feldman, M. and D. Audretsch (1999) Innovation in Cities: Science-based Diversity, Specialization and Localized Competition. *European Economic Review*, 43(2), 409-429.

Fujita, M. and J.F. Thisse (1996) Economics of Agglomeration. *Journal of the Japanese and International Economies*, 10(4), 339-378.

Gallup, J.L., J. Sachs and A. Mellinger (1999) Geography and Economic Development. *International Regional Science Review*, 22(2), 179-232.

Grossman, G. and E. Helpman (1991) *Innovation and Growth in the Global Economy*. Cambridge, MIT Press.

Hall, B.H., A.B. Jaffe and M. Trajtenberg (2001) The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools, Working Paper No. 8498, National Bureau of Economic Research.

Hall, B. and R. Ziedonis (2001) The Patent Paradox Revisited: an Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. *Rand Journal of Economics*, 32(1), 101-128.

Jacobs, J. (1969) *The Economy of Cities*. New York, Random House.

Jaffe, A., M. Trajtenberg, and R. Henderson (1993) Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics*, 108(3), 577-598.

Johnson, D. and A. Brown (2002) How the West Was Won: Regional and Industrial Inversion in U.S. Patent Activity, Wellesley College Working Paper.

Kortum, S. (1997) Research, Patenting and Technological Change. *Econometrica*, 65(6), 1389-1419.

Kortum, S. and J. Lerner (1998) Stronger Protection or Technological Revolution: What is Behind the Recent Surge in Patenting? *Carnegie-Rochester Conference Series on Public Policy*, 48(0), 247-304.

Loewy, M.B. and D.H. Papell (1996) Are U.S. Regional Incomes Converging? Some Further Evidence, *Journal of Monetary Economics*, 38(3), 587-598.

Lumsdaine, R.L. and D. Papell, (1997) Multiple Trend Breaks and the Unit Root Hypothesis. *Review of Economics and Statistics*, 79(2), 212-218.

Markusen, A., P. Hall and A. Glasmeier (1986) *High Tech America: The What, How, Where and Why of the Sunrise Industries*. Boston, Allen & Unwin.

National Science Foundation (2001) *National Patterns of R&D Resources: 2000 Data Update*. Arlington, VA (NSF 01-309). http://www.nsf.gov/sbe/srs/nsf01309/start.htm.

National Science Foundation (1999) *What is the State Government Role in the R&D Enterprise?* Arlington, VA (NSF 99-348).

Nelson, R. and G. Wright (1992) The Rise and Fall of American Technological Leadership: The Post-War Era in Historical Perspective. *Journal of Economic Literature*, 30(4), 1931-1964.

Ng, S., and P. Perron (1995) Unit Root Tests in ARMA Models with Data-dependent Methods for Lag Selection of the Truncation Lag. *Journal of the American Statistical Association*, 90(429), 268-81.

Perron, P. (1989) The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis. *Econometrica*, 57(6), 1361-1401.

Pisano, G. (2002) Pharmaceutical Biotechnology, in B. Steil, D. Victor, R. Nelson (eds.) *Technological Innovation and Economic Performance*, Princeton University Press, Princeton.

Quah, D. (1996) Aggregate and Regional Disaggregate Fluctuations. *Empirical Economics*, 21(1), 137-159.

Quah, D. (1992) International Patterns of Growth: I Persistence in Cross-country Disparities, London School of Economics Working Paper.

Romer, P. (1990) Endogenous Technological Change, *Journal of Political Economy*, 98(5), S71-102.

Said, S.E. and D.A. Dickey (1984) Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order. *Biometrika*, 71(3), 599-607.

Smith, P. (1999) Do Knowledge Spillovers Contribute to U.S. State Output and Growth? *Journal of Urban Economics*, 45(2), 331-353.

Sokoloff, K. (1988) Inventive Activity in Early Industrial America: Evidence from Patent Records, 1790-1846, *Journal of Economic History*, 48(4), 813-850.

Suarez-Villa, L. (2000) *Invention and the Rise of Technocapitalism*. Lanham, Rowman & Littlefield.

Tomljanovich, M. and Vogelsang, T. (2002) Are U.S. Regions Converging? Using New Econometric Methods to Examine Old Issues, *Empirical Economics*, 27(1), 49-62.

Varga, A. (1999) Time-Space Patterns of U.S. Innovation: Stability or Change? in M.M. Fischer and L. Suarez-Villa (eds.) *Innovation, Networks and Localities*, Springer, Berlin.

Zivot, E. and D.W.K Andrews (1992) Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit Root Hypothesis. *Journal of Business and Economic Statistics*, 10(3), 251-270.

Figure 1a

Log Relative Patent per 100,000 Inhabitants, 1929-1997
Leading Regions

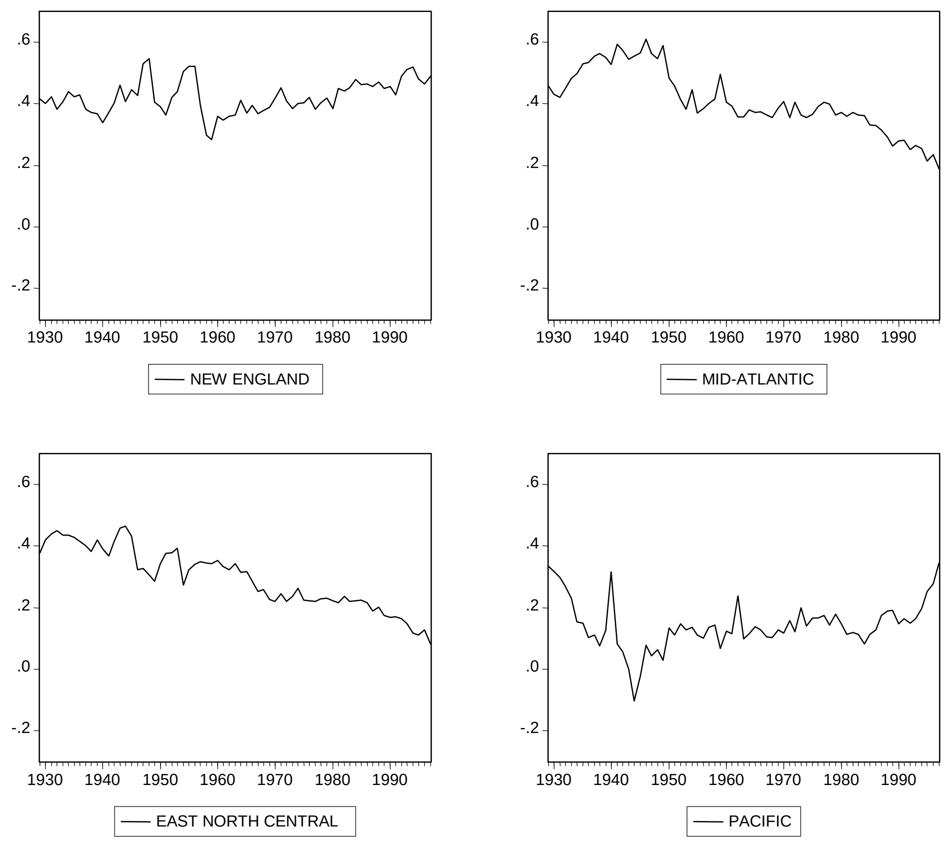

Figure 1b

Log Relative Patent per 100,000 Inhabitants, 1929-1997
Lagging Regions

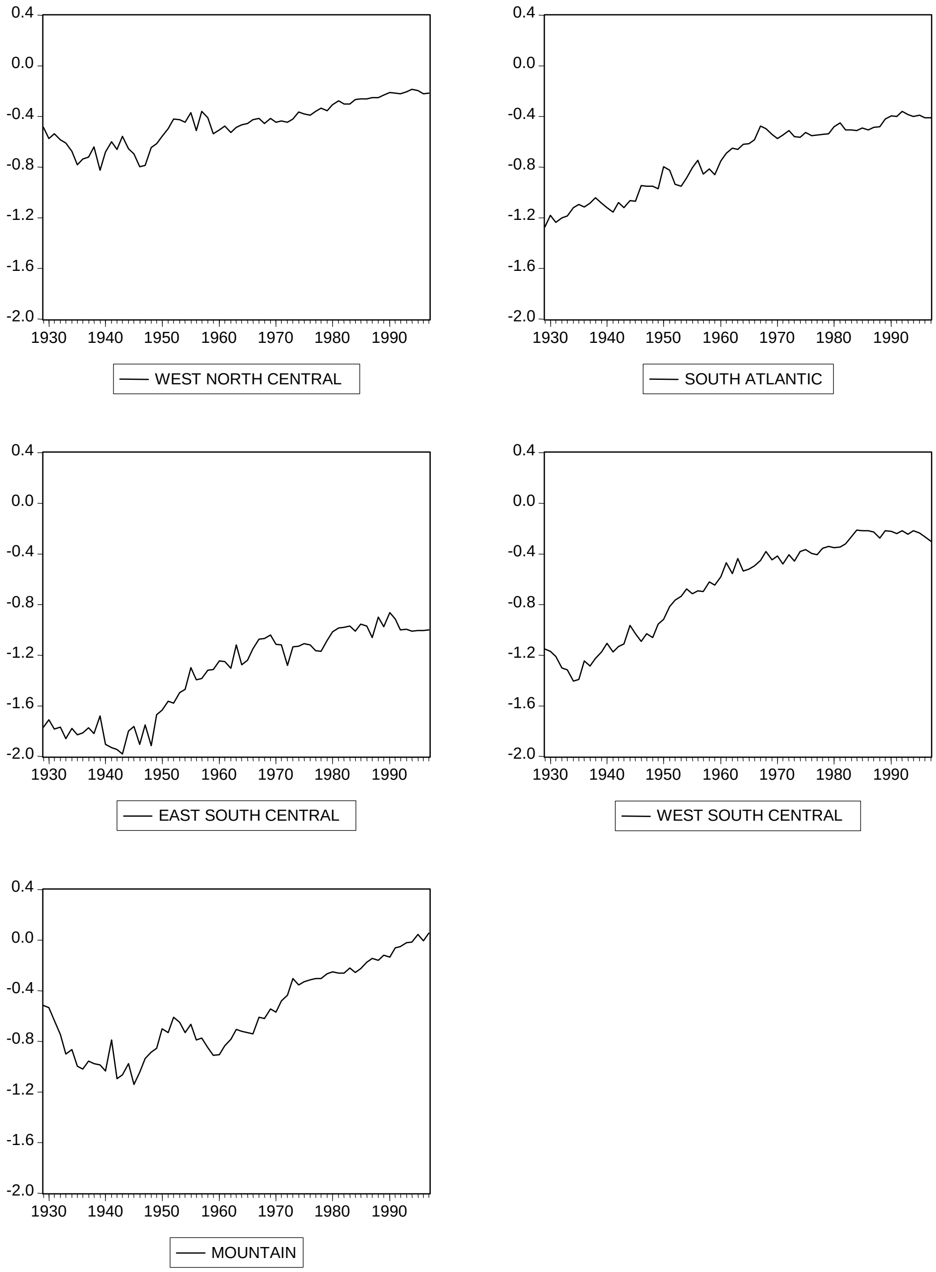

Table 1. Growth Rates of Total Patents and Patent per 100,000 Inhabitants, 1929-35 to 1991-97

	Growth Rate, 1929-35 to 1991-97			
Region/State	Total Patents	Patents per 100,000 inhabitants	Patents per 100,000 inhabitants	
			1929-35	1991-97
US	**28.63**	**-38.15**	**34.89**	**21.58**
New England	**7.12**	**-33.55**	**52.69**	**35.02**
Connecticut	15.29	-42.61	79.15	45.42
Maine [1/]	5.74	-32.42	12.54	8.48
Massachusetts	-2.84	-31.42	55.10	37.79
New Hampshire	113.70	-11.97	38.58	33.97
Rhode Island	-35.79	-56.92	50.49	21.75
Vermont [1/]	173.04	65.71	17.31	28.68
Middle Atlantic	**-29.70**	**-50.60**	**55.57**	**27.45**
New Jersey	-5.50	-51.30	76.94	37.46
New York	-40.24	-57.46	61.55	26.18
Pennsylvania	-27.45	-41.19	38.71	22.76
East North Central	**-21.96**	**-54.04**	**53.50**	**24.59**
Illinois	-40.05	-60.84	63.07	24.69
Indiana	-8.16	-47.70	35.91	18.78
Michigan	16.58	-41.74	51.72	30.13
Ohio	-33.42	-59.79	57.62	23.17
Wisconsin	-4.54	-43.79	41.82	23.51
West North Central [1/]	**23.63**	**-8.66**	**19.15**	**17.50**
Iowa [1/]	-14.80	-25.51	18.63	13.88
Kansas [1/]	9.62	-20.84	12.82	10.15
Minnesota [1/]	138.91	37.58	25.61	35.24

Table 1, continued.

Region/State	Growth Rate, 1929-35 to 1991-97: Total Patents	Growth Rate, 1929-35 to 1991-97: Patents per 100,000 inhabitants	Patents per 100,000 inhabitants: 1929-35	Patents per 100,000 inhabitants: 1991-97
Missouri [1/]	-25.38	-47.58	24.49	12.84
Nebraska [1/]	-15.25	-29.03	13.50	9.58
North Dakota [1/]	48.34	54.27	5.73	8.83
South Dakota [1/]	-38.41	-43.92	9.11	5.11
South Atlantic [1/]	**301.95**	**36.57**	**10.64**	**14.53**
Delaware	193.06	1.43	64.36	65.28
Florida [1/]	687.22	-14.49	16.07	13.75
Georgia [1/ 1/]	433.46	119.97	5.14	11.30
Maryland	115.69	-27.81	28.26	20.40
North Carolina [1/]	565.67	201.98	4.76	14.38
South Carolina [1/]	630.64	246.18	3.43	11.89
Virginia [1/]	291.09	47.12	8.86	13.04
West Virginia [1/]	-21.65	-26.51	11.28	8.29
East South Central [1/]	**116.03**	**36.82**	**5.85**	**8.00**
Alabama [1/]	134.87	46.67	4.54	6.65
Kentucky [1/]	37.28	-5.31	8.00	7.57
Mississippi [1/]	147.13	82.52	2.47	4.50
Tennessee [1/]	186.83	48.89	7.54	11.23
West South Central [1/]	**295.66**	**72.09**	**9.79**	**16.84**
Arkansas [1/]	114.36	58.37	3.11	4.92
Louisiana [1/]	194.43	45.89	6.69	9.76
Oklahoma [1/]	65.41	21.51	13.26	16.11
Texas [1/]	439.63	74.35	11.59	20.21

Table 1, continued.

	Growth Rate, 1929-35 to 1991-97			
Region/State	Total Patents	Patents per 100,000 inhabitants	Patents per 100,000 inhabitants	
			1929-35	1991-97
Mountain [1/]	**415.83**	**26.34**	**16.95**	**21.41**
Arizona [1/]	1508.31	65.52	13.60	22.52
Colorado [1/]	255.70	1.98	27.03	27.56
Idaho [1/]	482.47	131.68	12.65	29.32
Montana [1/]	46.02	-10.12	12.34	11.09
Nevada [1/]	726.21	-48.02	22.00	11.43
New Mexico [1/]	918.56	167.85	5.42	14.53
Utah [1/]	436.33	41.64	16.93	23.98
Wyoming [1/]	13.16	-47.77	16.62	8.68
Pacific	**184.12**	**-39.95**	**45.09**	**27.08**
California	194.36	-45.02	52.78	29.02
Oregon [1/]	167.54	-16.67	24.79	20.66
Washington [1/]	125.88	-33.22	29.08	19.42

Note: [1/] Denotes lagging region or state.

Table 2. Unit root tests for the log of U.S. patent per capita and log relative patent per capita, 1929-1997

Region	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
New England	1946	-1.921	0.765 [b/]	0.892 [b/]	0.669 [c/]	-0.000	-0.006	0.007 [b/]	6
	1960	(-6.25)	(5.97)	(6.47)	(6.18)	(-0.00)	(-2.83)	(6.20)	
Middle Atlantic	1949	-0.819 [b/]	0.435 [a/]	0.361	0.347 [b/]	0.003	-0.003	-0.008 [b/]	5
	1975	(-6.59)	(7.06)	(5.67)	(6.60)	(1.62)	(-2.63)	(-6.58)	
East North Central	1945	-1.133	0.440	0.411	0.325	0.007	-0.002	-0.005	8
	1966	(-4.54)	(4.16)	(4.18)	(4.30)	(1.70)	(-1.75)	(-4.29)	
West North Central[1/]	1945	-1.005 [b/]	-0.685 [a/]	-0.754 [b/]	-0.533 [b/]	0.001	0.030	0.009 [b/]	3
	1958	(-6.58)	(-6.73)	(-6.19)	(-6.48)	(0.18)	(5.25)	(6.14)	
South Atlantic[1/]	1945	-0.617	-0.681	-0.572	-0.378	0.001	0.006	0.004	3
	1960	(-4.47)	(-4.10)	(-3.91)	(-3.91)	(0.30)	(1.78)	(2.84)	
East South Central [1/]	1939	-0.804	-1.509 [b/]	-1.613	-0.942	0.039	0.025 [b/]	0.007	6
	1970	(-5.52)	(-5.53)	(-5.49)	(-5.44)	(1.39)	(5.69)	(3.54)	
West South Central[1/]	1959	-0.531	-0.766 [b/]	-0.273	-0.097	0.016 [a/]	0.004	-0.004	1
	1982	(-5.45)	(-5.50)	(-4.58)	(-2.69)	(5.95)	(2.46)	(-1.31)	
Mountain[1/]	1946	-0.601	-0.535 [a/]	-0.462	-0.333	-0.008	-0.000	0.012	3
	1966	(-5.77)	(-6.09)	(-4.75)	(-4.67)	(-1.60)	(-0.14)	(4.55)	

Table 2, continued.

Region	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
Pacific	1939	-0.879 [b/]	0.286 [c/]	0.251	0.072	-0.023	-0.059	0.002	0
	1945	(-6.63)	(4.84)	(4.34)	(4.35)	(-3.53)	(-4.31)	(3.90)	
Critical Values	1%	-7.17	-6.07	-6.88	-7.26	-6.04	-6.17	-6.71	
			6.23	6.68	6.90	5.91	6.35	6.53	
	5%	-6.57	-5.08	-6.03	-6.15	-5.17	-5.74	-5.59	
			4.95	6.12	6.24	5.38	5.66	5.72	
	10%	-6.28	-4.50	-5.65	-5.69	-4.52	-5.30	-5.16	
			4.55	5.75	5.81	4.77	5.31	5.30	

Notes: [1/] Denotes lagging region. The last six rows report the critical values. [a/] Significant at the 1% level. [b/] Significant at the 5% level. [c/] Significant at the 10% level. The numbers in parentheses are t-statistics.

Table 3. Unit root tests for the log relative patent per capita, 1929-1997

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
New England									
Connecticut	1941	-0.997	0.833 [b/]	0.915	0.940	0.000	-0.003	-0.016	1
	1982	(-5.54)	(5.61)	(5.52)	(5.70)	(0.06)	(-3.83)	(-4.79)	
Maine[1/]	1958	-1.522	-1.748 [b/]	-2.122	-1.385	0.000	0.012	-0.001	5
	1982	(-5.17)	(-5.24)	(-5.37)	(-4.49)	(0.05)	(2.96)	(-0.10)	
Massachusetts	1957	-0.854 [a/]	0.763 [b/]	0.582	0.854	-0.002	0.015 [b/]	0.009	0
	1962	(-7.63)	(5.39)	(5.47)	(5.71)	(-0.98)	(5.92)	(4.11)	
New Hampshire	1951	-2.204	0.397	-1.751 [b/]	-0.086	-0.161 [b/]	0.045 [a/]	0.101 [b/]	4
	1980	(-5.96)	(3.29)	(-6.76)	(-1.22)	(-5.80)	(6.97)	(6.19)	
Rhode Island	1956	-1.061 [b/]	0.581 [c/]	0.326	-0.762	0.032	-0.036	0.064	4
	1987	(-6.61)	(4.72)	(2.15)	(-4.08)	(3.13)	(-3.33)	(3.45)	
Vermont[1/]	1951	-0.737	-0.637	-0.127	-0.530	0.007	-0.058	0.023	1
	1963	(-4.76)	(-4.43)	(-1.16)	(-3.99)	(1.27)	(-3.47)	(4.28)	
Middle Atlantic									
New Jersey	1947	-0.542	0.401 [b/]	0.510 [c/]	0.554 [c/]	0.011	-0.002	-0.013 [b/]	0
	1974	(-5.97)	(5.88)	(5.57)	(6.04)	(4.18)	(-2.00)	(-5.70)	

Table 3, continued.

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
New York	1949	-0.744	0.504 [b/]	0.322	0.073	0.000	-0.008	0.005	5
	1983	(-5.17)	(5.52)	(3.93)	(2.34)	(0.01)	(-3.42)	(1.42)	
Pennsylvania	1953	-0.750	0.085	0.094	0.230	-0.003	0.004	-0.016	1
	1982	(-4.96)	(3.78)	(4.96)	(4.58)	(-2.55)	(3.19)	(-4.74)	
East North Central									
Illinois	1952	-0.736 [a/]	0.449 [a/]	0.831 [a/]	0.419 [a/]	-0.002	-0.432 [a/]	-0.008 [a/]	0
	1954	(-9.86)	(9.24)	(8.26)	(10.23)	(-1.70)	(-7.52)	(-9.66)	
Indiana	1958	-1.369	0.011	-0.018	0.073	-0.003	-0.004	-0.018	5
	1981	(-6.27)	(0.55)	(-0.97)	(2.80)	(-2.31)	(-2.45)	(-4.88)	
Michigan	1945	-0.797 [b/]	0.485 [b/]	0.285	0.321	-0.001	0.007	0.002	0
	1966	(-6.98)	(5.79)	(4.88)	(5.53)	(-0.11)	(4.12)	(2.05)	
Ohio	1963	-0.828	0.431 [b/]	0.226	0.237	-0.004	-0.003	-0.014	1
	1981	(-5.27)	(5.18)	(4.21)	(4.79)	(-3.73)	(-1.35)	(-4.45)	
Wisconsin	1946	-0.800	0.146	0.136	-0.094	-0.014	-0.004	0.008	3
	1973	(-5.99)	(3.38)	(4.74)	(-3.19)	(-2.98)	(-2.66)	(3.82)	

Table 3, continued.

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
West North Central[1/]									
Iowa[1/]	1947	-0.597 [c/]	-0.846 [c/]	-1.191	-0.728	-0.023	0.030 [c/]	0.009	0
	1981	(-6.37)	(-5.07)	(-5.51)	(-5.46)	(-1.23)	(5.32)	(4.05)	
Kansas[1/]	1947	-0.868 [a/]	-1.335 [a/]	-1.134 [c/]	-0.652 [c/]	-0.010	0.009	-0.013 [b/]	2
	1972	(-7.50)	(-6.60)	(-5.99)	(-5.85)	(-1.40)	(3.28)	(-5.92)	
Minnesota[1/]	1939	-0.909 [a/]	-0.130	-0.328	-0.009	-0.048 [c/]	0.013	0.020 [b/]	0
	1970	(-8.21)	(-1.95)	(-5.42)	(-0.26)	(-4.54)	(4.88)	(6.01)	
Missouri[1/]	1945	-0.949 [a/]	-0.382 [a/]	-0.504 [b/]	-0.347 [a/]	0.005	0.041	-0.004	0
	1955	(-8.41)	(-6.39)	(-6.62)	(-7.70)	(1.21)	(4.41)	(-3.16)	
Nebraska[1/]	1949	-1.044 [c/]	-0.972 [a/]	-1.239 [c/]	-0.931	-0.041	0.003	0.005	1
	1977	(-6.34)	(-6.76)	(-5.82)	(-5.42)	(-4.18)	(0.85)	(0.91)	
North Dakota[1/]	1940	-1.895 [a/]	-3.415 [a/]	-3.636 [a/]	-2.817 [a/]	-0.072	0.072	0.027 [c/]	2
	1958	(-8.07)	(-7.85)	(-7.56)	(-7.93)	(-1.94)	(4.80)	(5.50)	
South Dakota[1/]	1944	-1.386	-2.205 [a/]	-2.947	-1.989 [c/]	-0.032	0.097	0.002	4
	1958	(-5.73)	(-6.16)	(-5.64)	(-5.80)	(-1.54)	(5.13)	(0.91)	

Table 3, continued.

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
South Atlantic[1/]									
Delaware	1933	-0.424	0.096	0.629	0.682	0.059	-0.003	-0.063	0
	1990	(-5.37)	(0.67)	(5.61)	(4.68)	(1.11)	(-2.83)	(-2.82)	
Florida[1/]	1942	-1.407 [a/]	-1.121 [a/]	-1.600 [a/]	-1.230 [b/]	-0.025	0.033 [b/]	0.017 [a/]	4
	1956	(-7.43)	(-7.50)	(-7.56)	(-7.25)	(-2.64)	(5.92)	(6.88)	
Georgia[1/]	1944	-1.862	-3.598 [a/]	-3.512 [b/]	-3.217 [c/]	0.024	0.051	0.053 [b/]	5
	1957	(-6.22)	(-6.17)	(-6.16)	(-6.14)	(2.50)	(5.29)	(6.37)	
Maryland[1/]	1945	-0.835 [a/]	-0.121	-0.038	-0.152	-0.008	0.002	0.009	0
	1983	(-7.18)	(-2.20)	(-1.16)	(-2.73)	(-1.59)	(1.32)	(1.42)	
North Carolina[1/]	1947	-0.722 [c/]	-1.418 [a/]	-1.229 [c/]	-0.704 [b/]	0.000	0.026 [c/]	0.019 [c/]	0
	1972	(-6.39)	(-6.32)	(-6.00)	(-6.21)	(0.10)	(5.45)	(5.72)	
South Carolina[1/]	1947	-0.933	-2.112	-1.903	-0.633	-0.007	0.036	0.008	4
	1985	(-4.16)	(-3.96)	(-3.79)	(-3.68)	(-0.91)	(3.77)	(0.84)	
Virginia[1/]	1939	-0.719 [c/]	-1.080 [a/]	-1.068 [b/]	-0.371	0.023	0.024 [b/]	-0.001	0
	1964	(-6.52)	(-6.43)	(-6.52)	(-5.49)	(2.44)	(6.10)	(-0.44)	

Table 3, continued.

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
West Virginia[1/]	1947	-0.570	-1.195 [b/]	-1.503 [c/]	-0.938 [c/]	-0.002	0.039	-0.001	1
	1968	(-4.33)	(-5.57)	(-5.86)	(-5.94)	(-0.18)	(5.17)	(-0.45)	
East South Central[1/]									
Alabama[1/]	1948	-0.850	-1.854 [b/]	-1.402	-0.726	0.008	0.012	-0.028	1
	1984	(-5.70)	(-5.73)	(-5.23)	(-4.26)	(1.09)	(3.35)	(-2.43)	
Kentucky[1/]	1947	-0.503	-1.201	-1.530	-0.688	-0.015	0.041	-0.003	1
	1956	(-5.05)	(-4.38)	(-4.39)	(-4.23)	(-1.72)	(3.96)	(-1.78)	
Mississippi[1/]	1945	-1.004	-2.824 [b/]	-2.859 [c/]	-2.540 [c/]	0.012	0.089	0.025 [b/]	5
	1956	(-5.95)	(-5.76)	(-5.68)	(-6.06)	(0.75)	(4.25)	(6.12)	
Tennessee[1/]	1939	-0.820	-1.315 [b/]	-1.422 [c/]	-0.840	0.042	0.033 [b/]	0.009	3
	1960	(-5.84)	(-5.53)	(-6.02)	(-5.62)	(2.19)	(5.94)	(4.18)	
West South Central[1/]									
Arkansas[1/]	1945	-0.792 [a/]	-1.932 [a/]	-1.600 [a/]	-0.960	-0.006	0.008	-0.043	0
	1989	(-7.38)	(-7.30)	(-6.98)	(-5.46)	(-0.83)	(3.68)	(-1.96)	
Louisiana[1/]	1945	-0.837	-1.433 [b/]	-1.099	-0.380	0.004	0.012	-0.059	1
	1989	(-5.60)	(-5.65)	(-5.28)	(-3.34)	(0.68)	(4.52)	(-3.35)	

Table 3, continued.

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
Oklahoma[1/]	1960	-0.690	-0.831 [b/]	0.203	0.247	0.032 [b/]	-0.006	-0.046	1
	1983	(-5.45)	(-5.40)	(3.62)	(3.42)	(5.74)	(-1.66)	(-4.93)	
Texas[1/]	1950	-0.698 [b/]	-0.798 [a/]	-0.471	-0.372 [c/]	0.007	-0.001	0.010 [c/]	0
	1959	(-6.60)	(-6.64)	(-5.05)	(-5.88)	(3.75)	(-0.09)	(5.56)	
Mountain[1/]									
Arizona[1/]	1941	-0.922	-0.855 [c/]	-1.303	0.000	-0.025	0.033 [c/]	0.003	4
	1980	(-5.53)	(-5.00)	(-5.36)	(0.01)	(-1.54)	(5.45)	(0.48)	
Colorado[1/]	1946	-0.664	-0.228	-0.194	-0.146	-0.021	-0.007	0.011	4
	1968	(-5.63)	(-3.41)	(-2.98)	(-2.80)	(-2.91)	(-2.45)	(3.74)	
Idaho[1/]	1932	-0.702	-0.539	-0.986 [c/]	-0.152	-0.006	0.009	0.063	0
	1988	(-6.16)	(-1.56)	(-5.96)	(-0.90)	(-0.04)	(3.99)	(2.07)	
Montana[1/]	1948	-1.195 [b/]	-1.373 [a/]	-0.871	-1.851 [b/]	-0.008	-0.045	0.036 [b/]	1
	1964	(-7.06)	(-7.04)	(-5.26)	(-6.79)	(-0.88)	(-3.97)	(5.89)	
Nevada[1/]	1956	-0.947 [c/]	-1.061 [c/]	-1.261 [c/]	-0.911	0.038	0.034	0.025	4
	1984	(-6.36)	(-4.74)	(-5.78)	(-5.19)	(2.99)	(4.73)	(1.55)	

Table 3, continued.

Region/State	TB1 TB2	ρ	μ_1	μ_2	μ_3	β_1	β_2	β_3	k
New Mexico[1/]	1936	-1.209[b/]	-1.964[a/]	-1.837[b/]	-1.230[b/]	-0.117	0.028	0.031	1
	1969	(-7.03)	(-6.29)	(-6.35)	(-6.45)	(-2.61)	(4.88)	(5.16)	
Utah[1/]	1949	-0.823	-1.275[a/]	-1.472	-0.516	0.047	0.025	0.021	1
	1961	(-5.34)	(-6.64)	(-5.05)	(-3.67)	(1.40)	(5.27)	(3.78)	
Wyoming[1/]	1932	-1.235[a/]	-0.494	-1.418[a/]	-1.401[a/]	-0.107	0.012	0.008	0
	1958	(-10.51)	(-1.56)	(-9.32)	(-9.52)	(-0.73)	(2.17)	(2.72)	
Pacific									
California	1939	-0.901	0.411[c/]	0.441	0.209	-0.022	-0.069	0.001	1
	1945	(-5.59)	(4.57)	(5.16)	(5.34)	(-2.71)	(-4.59)	(1.21)	
Oregon[1/]	1948	-0.546	-0.199	-0.183	-0.037	-0.011	-0.002	0.003	0
	1983	(-5.63)	(-4.10)	(-3.77)	(-0.69)	(-2.55)	(-1.67)	(0.50)	
Washington[1/]	1946	-0.569	-0.158	-0.178	-0.259	-0.018	-0.007	0.010	2
	1972	(-5.22)	(-3.65)	(-3.29)	(-3.95)	(-3.02)	(-3.59)	(3.47)	

Notes: [1/] Denotes lagging state. The critical values appear in the last six rows of Table 2. [a/] Significant at the 1% level. [b/] Significant at the 5% level. [c/] Significant at the 10% level. The numbers in parentheses are t-statistics.

Table 4. Summary of results

	β-convergence [a]				
Region/State	Pre-1st Break	Pre-2nd Break	Post-Breaks	Stochastic Convergence [b]	Evidence Convergence [c]
New England	**c**	**c**	**D**	**No**	
Connecticut	d			No	
Maine [1]	c			No	
Massachusetts	c	d		Yes	weak
New Hampshire	c	C	c	No	
Rhode Island	d			Yes	
Vermont [1]				No	
Middle Atlantic	**d**			**Yes**	**weak**
New Jersey	d	c	C	No	
New York	d		E	No	
Pennsylvania	E	E		No	
East North Central				**No**	
Illinois	c	C	C	Yes	strong
Indiana	E	E	E	No	
Michigan	c			Yes	weak
Ohio	c			No	
Wisconsin				No	

Table 4, continued.

	β-convergence [a/]				
Region/State	Pre-1st Break	Pre-2nd Break	Post-Breaks	Stochastic Convergence [b/]	Evidence Convergence [c/]
West North Central [1/]	**c**	**c**	**C**	**Yes**	**strong**
Iowa [1/]	c	c		Yes	moderate
Kansas [1/]	c	c	D	Yes	moderate
Minnesota [1/]	c		c	Yes	moderate
Missouri [1/]	c	c	c	Yes	strong
Nebraska [1/]	c	c		Yes	moderate
North Dakota [1/]	d	c	C	Yes	moderate
South Dakota [1/]	d		c	No	
South Atlantic [1/]				**No**	
Delaware	E			No	
Florida [1/]	c	C	C	Yes	strong
Georgia [1/]	c	C	C	No	
Maryland [1/]		E		Yes	weak
North Carolina [1/]	c	C	C	Yes	strong
South Carolina [1/]				No	
Virginia [1/]	c	C		Yes	moderate
West Virginia [1/]	c	c	d	Yes	moderate

Table 4, continued.

	β-convergence [a/]				
Region/State	Pre-1st Break	Pre-2nd Break	Post-Breaks	Stochastic Convergence [b/]	Evidence Convergence [c/]
East South Central [1/]	**c**	**c**		**No**	
Alabama [1/]	c			No	
Kentucky [1/]				No	
Mississippi [1/]	c	C	C	No	
Tennessee [1/]	c	C		No	
West South Central [1/]	**C**		**E**	**No**	
Arkansas [1/]	d	d		Yes	
Louisiana [1/]	c			No	
Oklahoma [1/]	C			No	
Texas [1/]	c		C	Yes	moderate
Mountain [1/]	**c**			**No**	
Arizona [1/]	c	c	E	No	
Colorado [1/]				No	
Idaho [1/]		c		No	
Montana [1/]	c		C	Yes	moderate
Nevada [1/]	c	c		Yes	moderate
New Mexico [1/]	c	C	c	Yes	strong
Utah [1/]	c			Yes	weak
Wyoming [1/]		C	c	No	

Table 4, continued.

Region/State	β-convergence [a] Pre-1st Break	Pre-2nd Break	Post-Breaks	Stochastic Convergence [b]	Evidence Convergence [c]
Pacific	**c**		**E**	**Yes**	**moderate**
California	c			No	
Oregon [1]			E	No	
Washington [1]				No	

Notes:[1] Denotes lagging region or state. [a] The following are adopted from Tomljanovich and Vogelsang (2002): *C* (*D*) denotes coefficient estimates are consistent with *β-convergence* (divergence) and are statistically significant at least at the 10% level. *c* (*d*) denotes coefficient estimates are consistent with *β-convergence* (divergence) and only one estimate is statistically significant at least at the 10% level. *E* denotes coefficient estimates are very small in magnitude and statistically insignificant indicative that *β-convergence* has occurred. [b] Yes denotes coefficient estimates consistent with *stochastic convergence*. [c] Strong evidence in favor of convergence when stochastic convergence is found and three entries in columns two to four are *c*'s (or *E*'s). Moderate evidence in favor of convergence when stochastic convergence is found and two entries in columns two to four are *c*'s (or *E*'s). Weak evidence in favor of convergence when stochastic convergence is found and only one entry in columns two to four is a *c* (or *E*).

Table 5. State distance to California and Spearman correlation coefficients

Region/State	Distance to California (in miles)	Spearman correlation coefficients 1963-1969	1970-1976	1977-1983	1984-1990	1991-1997
New England						
Maine	2,671	0.162	0.104	0.163	-0.013	0.337 [b/]
Vermont	2,532	0.460 [a/]	0.223	0.231	0.053	0.213
West North Central						
Iowa	1,484	0.331 [b/]	0.376 [b/]	0.528	0.260 [c/]	0.227
Kansas	1,387	0.013	-0.184	0.044	-0.079	-0.020
Minnesota	1,522	0.272 [c/]	0.174	0.069	0.209	0.028
Missouri	1,579	-0.373 [b/]	-0.407 [a/]	-0.495 [a/]	-0.411 [a/]	-0.334 [b/]
Nebraska	1,325	0.109	0.121	0.151	-0.024	-0.087
North Dakota	1,193	0.104	0.176	0.237	0.301 [c/]	0.133
South Dakota	1,164	0.101	0.354 [b/]	0.145	0.196	0.241
South Atlantic						
Florida	2,178	0.323 [b/]	0.620 [a/]	0.678 [a/]	0.650 [a/]	0.679 [a/]
Georgia	2,083	-0.045	-0.138	-0.167	-0.307 [b/]	-0.433 [a/]
Maryland	2,403	0.453 [a/]	0.521 [a/]	0.385	0.316 [b/]	0.121
North Carolina	2,348	-0.360 [b/]	-0.286 [c/]	-0.389	-0.292 [c/]	-0.485 [a/]
South Carolina	2,268	-0.353 [b/]	-0.370 [b/]	-0.306	-0.263 [c/]	-0.395 [a/]
Virginia	2,377	0.245	0.362 [b/]	0.392	0.435 [a/]	0.173
West Virginia	2,143	-0.612 [a/]	-0.606 [a/]	-0.607	-0.493 [a/]	-0.481 [a/]

Table 5, continued.

Region/State	Distance to California (in miles)	Spearman correlation coefficients 1963-1969	1970-1976	1977-1983	1984-1990	1991-1997
East South Central						
Alabama	2,017	-0.175	0.137	0.315	0.088	-0.032
Kentucky	1,947	-0.081	0.085	0.109	0.050	-0.098
Mississippi	1,806	0.221	0.066	0.215	0.073	0.212
Tennessee	1,905	-0.599 [a/]	-0.572 [a/]	-0.621 [a/]	-0.428 [a/]	-0.669 [a/]
West South Central						
Arkansas	1,632	0.161	0.250	0.311 [b/]	0.406 [a/]	0.121
Louisiana	1,810	-0.429 [a/]	-0.424 [a/]	-0.295 [c/]	-0.261 [c/]	-0.142
Oklahoma	1,338	-0.102	-0.265 [c/]	-0.030	-0.061	-0.123
Texas	1,464	0.263 [c/]	0.403 [a/]	0.215	0.338 [b/]	0.295 [c/]
Mountain						
Arizona	629	0.610 [a/]	0.623 [a/]	0.615 [a/]	0.536 [a/]	0.699 [a/]
Colorado	894	0.454 [a/]	0.470 [a/]	0.349 [b/]	0.590 [a/]	0.562 [a/]
Idaho	443	0.066	0.144	0.178	0.373 [b/]	0.387 [a/]
Montana	733	0.052	0.093	0.216	0.155	0.116
Nevada	101	0.109	0.059	0.086	0.148	0.127
New Mexico	878	0.621 [a/]	0.313 [b/]	0.535 [a/]	0.490 [a/]	0.472 [a/]
Utah	531	0.308 [b/]	0.477 [a/]	0.250	0.487 [a/]	0.335 [b/]
Wyoming	903	-0.039	0.399 [a/]	0.280 [c/]	0.318 [b/]	0.248

Table 5, continued.

		Spearman correlation coefficients				
Region/State	Distance to California (in miles)	1963-1969	1970-1976	1977-1983	1984-1990	1991-1997
Pacific						
Oregon	446	0.264 [c/]	0.204	0.466 [a/]	0.541 [a/]	0.414 [a/]
Washington	589	0.253	0.388	0.527 [a/]	0.495 [a/]	0.540 [a/]

Notes: [a/] Significant at the 1% level. [b/] Significant at the 5% level. [c/] Significant at the 10% level. Source of data: Distance is from http://www.indo.com/distance/; patent specialization rankings are tabulated using patent data from U.S. Patent and Trademark Office, Information Product Division, *Patenting Trends in the U.S., 1998, State/Country Report- All Years, 1963-1998.* CD-Rom issued July 2000.

Table 6. Average share of sector in total state expenditure for R&D

By performing sector, 1987-1997 (in percent)

	Federal	Industry	Colleges and Universities
US	**8.80**	**74.62**	**11.72**
New England	**5.21**	**75.44**	**11.83**
Connecticut	1.16	87.28	11.13
Maine	5.14	66.31	16.94
Massachusetts	4.22	73.51	11.05
New Hampshire	9.52	73.33	16.41
Rhode Island	33.53	49.52	14.26
Vermont	1.65	82.17	15.19
Middle Atlantic	**3.11**	**83.61**	**10.53**
New Jersey	4.73	89.94	4.01
New York	1.29	80.35	14.17
Pennsylvania	3.78	80.50	13.31
East North Central	**3.77**	**83.96**	**9.43**
Illinois	1.12	77.83	10.94
Indiana	2.82	85.75	11.31
Michigan	0.84	92.87	5.92
Ohio	13.05	76.60	9.25
Wisconsin	1.86	75.09	22.47
West North Central	**2.82**	**78.13**	**18.74**
Iowa	3.16	62.92	30.53
Kansas	1.33	81.67	16.33
Minnesota	1.21	85.43	11.00
Missouri	2.52	81.65	14.95
Nebraska	9.43	36.61	52.11
North Dakota	23.98	28.35	47.36
South Dakota	25.60	30.70	41.43

Table 6, continued.

	Federal	Industry	Colleges and Universities
South Atlantic	**31.03**	**50.48**	**16.60**
Delaware	0.75	93.72	4.08
Florida	16.13	71.77	11.93
Georgia	10.13	57.92	31.53
Maryland	59.03	22.13	16.71
North Carolina	5.81	72.74	19.95
South Carolina	4.21	73.35	21.59
Virginia	39.61	42.49	11.31
West Virginia	25.08	48.41	14.06
East South Central	**25.20**	**53.37**	**19.65**
Alabama	38.43	44.80	15.48
Kentucky	5.82	67.49	26.37
Mississippi	48.23	18.29	32.08
Tennessee	8.09	68.77	20.13
West South Central	**6.88**	**71.12**	**20.11**
Arkansas	16.38	54.76	28.11
Louisiana	9.59	33.68	56.25
Oklahoma	7.29	63.69	26.48
Texas	6.38	74.47	17.19
Mountain	**12.23**	**60.51**	**13.84**
Arizona	8.70	70.92	17.91
Colorado	7.27	71.33	12.55
Idaho	3.35	90.51	5.67
Montana	22.82	28.06	41.09
Nevada	23.50	53.24	22.75
New Mexico	16.48	40.77	6.42
Utah	11.76	67.82	19.99

Table 6, continued.

	Federal	Industry	Colleges and Universities
Wyoming	14.21	23.61	49.03
Pacific	**5.47**	**78.94**	**7.41**
California	5.84	78.34	6.88
Oregon	6.31	65.75	24.83
Washington	2.80	85.28	7.92

Source: National Science Foundation (2001). *National Patterns of R&D Resources: 2000 Data Update*. Arlington, VA (NSF 01-309). http://www.nsf.gov/sbe/srs/nsf01309/start.htm.

Table 7. First and Second Break Occurrences

Period	First break	Second break
1930-1934	ID, WY, DE	
1935-1939	NM, MN, VI, TN, CA	
1940-1944	ND, CT, AZ, FL, SD, GA	
	MI, MO, MD, MS, AR, LA, WI, CO, WA,	
	NJ, IA, KS, NC, SC, WV, KY, AL, MT, OR,	
1945-1949	NY, UT	CA
1950-1954	TX, NH, VT, IL, PA	IL
1955-1959	RI, NE, NV, MA, ME, IN	MO, FL, KY, MS, GA, ND, SD, WY, TX
1960-1964	OK, OH	TN, UT, MA, VT, VA, MT
1965-1969		MI, WV, CO, NM
1970-1974		MN, NC, KS, WA, WI, NJ
1975-1979		NE
		NH, AZ, IN, OH, IA, CT, ME, PA, NY, MD,
1980-1984		OK, OR, AL, NV
		MD, OK, OR, AL, NV
1985-1989		SC, RI, ID, AR, LA, DE