Knowledge Matters:

The Long-Run Determinants of State Income Growth

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Abstract

Real average U.S. per capita personal income growth over the last 65 years exceeded 400 percent, However, while the stark income differences across states narrowed considerably between 1939 and 1976, since 1976, the standard deviation of per capita incomes at the state level has actually risen, as some higher-income states have seen their income levels rise relative to the median of the states. This paper seeks to understand the sources of these relative growth performances. A key contribution of this paper is that we estimate the magnitude of various growth factors by using an augmented growth model and a panel of the 48 contiguous states from 1939 to 2004. Specifically, we control for factors that previous researchers have argued were important: tax burdens, public infrastructure, size of private financial markets, rates of business failure, industry structure, climate, and knowledge stocks. Our results, which are robust to a wide variety of perturbations to the model, are easily summarized: A state's knowledge stocks (as measured by its stock of patents and its high school and college attainment rates) are the main factors explaining a state's relative per capita personal income.

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I. Introduction

Can states use economic development policy to boost the average personal income levels of their citizens? This is certainly a major aim of most state economic development policies; yet neoclassical growth theory does not offer much hope of success for such policies. It predicts that capital mobility alone will lead to fairly quick convergence in per capita personal incomes across U.S. states. Unlike nations, U.S. states lack barriers to the flow of information, labor, and capital across boundaries that could preclude convergence (Barro and Sala-i-Martin, 1991; 1992). In fact, many researchers have noted that the tendency toward convergence over time in the per capita income of U.S. states supports the neoclassical view, at least when compared to the international results (Caselli and Coleman, 2001).

However, this convergence is not complete, and it appears to have stalled since the late 1970s (see the top left panel of Figure 1). Many explanations have been offered for differences in economic performance at the state or metropolitan level, including differences in tax policy (Easterly and Sergion, 1993; Mofidi and Stone, 1990; Phillips and Gross, 1990), varying rates of investment in public infrastructure (Aschauer, 1989; Evans and Karras, 1994; Wylie, 1996; Munnell, 1990); past industry structure (Higgins, Levy, and Young, 2006); climate (Barro and Sala-i-Martin, 1991); financial markets and economic performance (Abrams et al., 1999; King and Levine, 1993; Levine, 1997; Montgomery and Wascher, 1988; Rousseau and Wachtel, 1998); and knowledge and technology (Glaeser and Saiz, 2004; Mankiw, Romer, and Weil, 1992; Florida, 2002).

We focus on knowledge and technology in this paper. Researchers have offered a variety of explanations for the mechanism underlying the positive statistical association between knowledge stocks and per capita personal incomes at the state level: (1) workers with more knowledge are more productive; (2) education and technology allow more people to be employed in high productivity jobs (Rangazas, 2005); (3) education and technology allow people to adapt in response to negative economic shocks (Saiz,); (4) education and technology make people more creative (Glaeser and Saiz, 2004); and (5) education and technology allow people to adopt new technology from other places (Benhabib and Speigel, 1994; Barro, 1997).

While some dissipation of education and knowledge stocks occurs, the diffusion across state borders is likely to be incomplete because not all people will migrate even when entities in other states pay higher wages for their education (Barro and Sala-i-Martin, 1991); because knowledge spillovers appear to decrease with distance (Griliches, 1979), and because there is very little evidence of externalities in human capital at the state level (Rangazas, 2005).

We embed a variety of state-specific labor augmenting factors into a standard neoclassical growth model to allow the state-specific component of the standard technology term to vary in a manner consistent with endogenous growth theory (see Romer, 1986). As factors, we include measures of states' knowledge stocks, along with other factors that have been argued to explain per capital personal income levels—public finance, business environment, and meteorological climate. We find that our empirical results are driven by our three measures of a state's stock of knowledge: the proportion of the population with at least a high school degree, the proportion of the state's population with at least a bachelor's degree, and the stock of patents held by people or businesses in the state.

This paper incorporates a couple of advances on the previous literature in this area. First, we examine a longer time period than previous researchers, exploring differences in relative levels of per capita income among the 48 contiguous states from 1939 to 2004, allowing us to tease out the effects of factors that have weaker effects on relative per capita income growth. Second, we control for all classes of variables that previous researchers have argued affect relative per capita income levels across states, including a state's tax burden, its investments in public infrastructure, the size of its private financial markets, its rate of business failure, its industry structure, and its climate (Barro and Sala-i-Martin, 1991; Glaeser and Saiz, 2004; Caselli and Coleman, 2001; Kim, 1998). This permits us to estimate the magnitude of the effect that investments in knowledge have relative to investments in the other factors that affect income growth.

We test for predetermination of the explanatory variables using instruments, based on lagged values of differing duration and show that five-year lags remove (statistically) the threat of endogeneity. This allows us to avoid a problem with many efforts to associate differences in knowledge stocks and levels of per capita personal income, the endogeneity of education outcomes (Bils and Klenow, 2000). An exogenous factor might make the level of per capita personal income in some states higher than other states. Those states might use that extra income to purchase more of the explanatory variables, leading them to be positively correlated with per capital personal income without these variables directly causing one state's per capita personal income to be higher than another's.

II. The Potential Role of Growth Factors on State Income Levels

We take Romer's (1986) critique of neoclassical growth theory to heart by including in our model measurable factors that might enter into the aggregate production function of that state. These factors do not reveal the actual process of resource diversion into productivity-enhancing activities but they can reveal value-producing differences in the underlying production function. Specifically, we embed a variety of labor-augmenting factors into a standard neoclassical growth model, allowing the state-specific component of the standard technology term to vary.

At any given time t, the income ($Y_{t,s}$) of state s is assumed to follow a Cobb-Douglas function of its capital ($K_{t,s}$) and labor ($L_{t,s}$).

$$Y_{t,s} = K_{t,s}{}^{\alpha}\left(L_{t,s}X_{t,s}^{\gamma}A_{t}\right)^{1-\alpha} \tag{1}$$

The equation also contains the familiar labor-augmenting rate of productivity growth in the national economy (A_t), which accounts for all increases in labor-augmenting productivity including the average of any state-specific labor-augmenting factors at time t. State-specific labor augmenting factors $X_{t,s,}$ allow for relative differences in the state-varying factors. Without the addition of these state-specific factors, this equation is completely standard in the international income convergence literature (Islam, 1995).[1] Although Islam and others have accounted for human capital differences in a similar manner, the data available for U.S. states are richer than what is available internationally, allowing us to examine a wider set of factors.[2]

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[1] For ease of exposition in the development of our model, we treat X as a single factor. It is straightforward, but more tedious, to reformulate our exposition by modeling X as a log-linear function of multiple factors, Z.

[2] More factors could be considered with a shorter period, but we believe that the longer period is more desirable because it provides more reliable estimates of the effects. Higgins, Levy, and Young (2006) follow this former approach using many factors in a shorter panel of U.S. county-level data.

Specifically, we examine a set of factors that might offer a production benefit, such as human capital or public infrastructure, and that are either a characteristic of the resident workforce or that are more available to that workforce than to other workforces. By construction, the aggregate productivity level (A_t) will capture the average effect over all 48 states of all such production amenities, while the state factors are measured relative to the overall average and thus have a mean of one. This construction makes the estimation of the X variable a between-state estimator of the full effects in cases where the X variable is likely to have general as well as relative effects.

There are other variables that we would have liked to have included in the model but that are unobserved. These missing variables could bias our results if they are correlated with the variables we include. As part of our efforts to explore the robustness of our results, we also employ a fixed effects estimator. This estimation approach controls for unobserved fixed-state effects, thus providing a powerful cross check of our findings.

U.S. states have few barriers to capital mobility, and this should speed their income convergence.[3] If we make the assumptions typical of the growth literature (see Islam, 1995), solve for the steady-state equilibrium, and allow for dynamic adjustment toward this steady-state equilibrium, we can obtain the following reduced-form equation,

$$\ln(y_{t,s}) = \beta_o + \beta_1 \ln y_{t-\tau,s} + \beta_2 \ln X_{t-\tau,s} + \beta_3 D_t + \upsilon_{t,s} \qquad (2)$$

[3] Income differences might be also countered by labor mobility, although relative housing costs and regional preferences might cause net flows to cease before labor mobility can offset the value of local amenities (Roback, 1982). Also, if the quality of the local workforce is the productive amenity (or dis-amenity), then mobility would not be induced either into or from an area.

where D_t is a set of T-1 time dummies, which capture all the national trends (in particular, inflation, technological progress, and the average effect of the *X* variable) and τ is the lag length (which will be discussed later).

The key feature of this equation is that it allows for the estimation of the state-specific effects jointly with the underlying convergence process. The existence of a labor-augmenting factor ($X_{t,s}$) introduces the possibility of persistently higher (or lower) per capita incomes if β_2 is nonzero. The literature on income convergence has varied on the functional form of the estimates, but most of the cross-sectional or panel results can be transformed to be similar to our estimation. Barro and Sala-i-Martin (1991) estimate the relationship non-linearly in order to focus on the adjustment parameter, but taking the log of their specification results in an algebraically equivalent form. β convergence, when the partial correlation between growth in income over time and its initial level is negative, is implied in our estimates when β_1 is less than 1. Islam (1995) raises the possibility of conditional convergence which adds a set of state-specific dummy variables to equation 2. We will consider this approach as an alternative to our baseline.

A critical issue to consider is the potential for X endogenously responding with the income level. If the *X* variable is exogenous, there is no need to use a lagged value as an instrument; just set $\tau = 0$. However, international growth studies clearly find problems with treating the likely *X* variables as exogenous (see, for example, Bils and Klenow, 2000). Current values of the *X* variables are likely to be a function of any difference in the states' past levels of the same *X*, realized current income, and some expectation of relative future income prospects of the region (represented below as a linear function of future income surprises).

$$E(\ln X_{t,s}) = a_{t-\tau} + \phi \ln X_{t-\tau,s} + \varphi \ln y_{t-\tau,s} + E(\ln e_{t,s}) + E\left(\sum_{i=0 \text{to} \tau} \eta_i \upsilon_{t-i,s} \right) \quad (3)$$

At some lag τ, however, it is likely that future errors (or innovations), $\upsilon_{t,s}$ are uncertain enough that they no longer alter the realizations of the *X* variables τ years. If *X* is predetermined in this sense at a τ-year lag, then the future value of the *X* variables is simplified:

$$E(\ln X_{t,s}) = a_{t-\tau} + \phi \ln X_{t-\tau,s} + \varphi \ln y_{t-\tau,s} \quad (3')$$

The second equality follows because for $E(X_{t,s})$ to be zero by construction, the expected innovation ($v_{t,s}$) will be zero for an appropriate *a*. We do not assume predetermination of the *X* variables; instead, we test whether this condition holds. Predetermined *X* variables allows for consistent and efficient estimation of (2) using OLS.

In order to evaluate the role of the variables in state-level σ convergence (Barro and Sala-i-Martin [1991]), we need to account for correlations between explanatory variables. Taking the standard deviation of both sides of equation (2) and focusing on the *X* variables results in the following relationship,

$$\begin{aligned} \text{var}(\ln \hat{y}_{t,s}) = {} & \text{var}(\hat{\beta}_o + \hat{\beta}_1 \ln y_{t-\tau,s} + \hat{\beta}_3 D_t) + \text{var}(\hat{\beta}_2 \ln X_{t-\tau,s}) \\ & + 2\,\text{cov}\left(\hat{\beta}_o + \hat{\beta}_1 \ln y_{t-\tau,s} + \hat{\beta}_3 D_t, \hat{\beta}_2 \ln X_{t-\tau,s}\right). \end{aligned} \quad (4)$$

We have every reason to suspect that the covariance in equation (4) will not be zero and may be quite important in the determination of income variation across states.

We will present many of our results in terms of the variance with and without particular components of *X*. For example, to estimate how much of the variation can be explained we exclude all of the *X* variables by setting their values to zero:

$$
\begin{aligned}
\operatorname{var}(\ln\hat{y}_{t,s}) - \operatorname{var}(\ln\hat{y}_{t,s} \mid \ln X_{t-\tau,s} = 0) &= \operatorname{var}(\hat{\beta}_o + \hat{\beta}_1 \ln y_{t-\tau,s} + \hat{\beta}_3 D_t) + \operatorname{var}(\hat{\beta}_2 \ln X_{t-\tau,s}) \\
&\quad + 2\operatorname{cov}\left(\hat{\beta}_o + \hat{\beta}_1 \ln y_{t-\tau,s} + \hat{\beta}_3 D_t, \hat{\beta}_2 \ln X_{t-\tau,s}\right) \\
&\quad - \operatorname{var}(\hat{\beta}_o + \hat{\beta}_1 \ln y_{t-\tau,s} + \hat{\beta}_3 D_t) \\
&= \operatorname{var}(\hat{\beta}_2 \ln X_{t-\tau,s}) \\
&\quad + 2\operatorname{cov}\left(\hat{\beta}_o + \hat{\beta}_1 \ln y_{t-\tau,s} + \hat{\beta}_3 D_t, \hat{\beta}_2 \ln X_{t-\tau,s}\right)
\end{aligned}
\tag{5}
$$

This approach summarizes both the direct effect of the *X* variables on expected income variation and the effects of covariation between *X* and income levels. In the results section, we report a variety of estimates of the standard deviations (the square root of the variance), which are calculated by zeroing out selected regressors, in order to illustrate their estimated effect on per capita personal income convergence.

III. A 60-Year Panel of State Data

One of our goals is to extend the sample back as far as possible so that we can study the long-run evolution of state per capita personal incomes and measure effects with greater precision. We also include explanatory variables that previous researchers have argued are important to sort out how much each factor drives state per capita personal income, and mitigate bias from omitted variables.

Our data is limited by the banking deposit information by state, which only goes back to 1934. As our baseline model has five-year lags, this means our first observations are from 1939. Our last observations are from 2004. Data availability also led us to consider only 48 contiguous states because data for Alaska, Hawaii, and the District of Columbia are incomplete.

Our measure of a state's economic performance is per capita personal income, and the dependent variable is constructed by taking the natural log of the ratio of the Bureau of Economic Analysis's personal income series and the Census Bureau's population estimate for a given state at time *t*.

We include several explanatory variables that might alter convergence rates across states. All of these regressors are transformed as the natural log of the state's value at a given time, divided by the population-weighted average for all of the states in the sample. Thus, the average effect for a particular untransformed variable is captured by the year dummies, while the regressor captures that variable's relative effect.

Knowledge and Technology

Two of these variables measure educational attainment: the proportion of a state's population with at least a high school degree, and the proportion with at least a bachelor's degree. For 1979-2004 our source for these data is the annual Current Population Survey. For prior years, decennial data are available from the Census Bureau, which we interpolate as required for intermediate years. Because educational attainment moves only slowly over time, the interpolated values (and the extrapolated values for 1934) are reasonable.

We also measure the state's stock of patents to proxy for a state's ability to innovate new products and production techniques. The total number of patents by state is available in the *Annual Report of the Commissioner of Patents and USPTO* for the years 1917 to 2001. To calculate our stock variable we employ a perpetual-inventory approach. To estimate the initial stock for a given state, we take the average of the total number of patents issued from 1917 to 1919 and divide by an assumed depreciation rate. For subsequent years, a given year's stock is equal to the previous year's stock times the depreciation rate plus the number of patents issued in that year.

Our baseline model assumes a 5 percent depreciation rate. Faster assumed depreciation rates make the initial stock estimates less important. With a 5 percent depreciation rate, only 46 percent of the initial stocks are left in each state's patent stock in 1934, the first lag used. The assumed depreciation rate does not appear to be critical because we obtain very similar results for a wide range of depreciation rates (1 percent to 100 percent).

Public Finance

We include a measure of tax rates (Mofidi and Stone, 1990; Phillips and Gross, 1995): a state's total tax revenue (from Financial Statistics of States) net of severance taxes (in the early years from the Census Bureau and in later years from the Department of Energy) over the state's personal income.[4]

We include a measure of infrastructure expenditures (Aschauer, 1990; Wylie, 1996). Our proxy for public capital, highway capital, is constructed using a perpetual-inventory approach on data on highway spending from the Financial Statistics of States. The data become available for states in various years from 1917 to 1925. The initial stock for a state is calculated as the average of that state's first three years of observations divided by the assumed rate of depreciation. In our baseline model, we set depreciation equal to 5 percent, but, as with patent stocks, our results are robust over a wide range of values.

[4] We need to emphasize that this variable is not the tax rate on labor. It is a measure of a state's overall tax burden, but it does not control for how those taxes are actually levied, which could be important. In addition, this variable is likely to approximate current state spending.

Business Environment

We measure private financial markets within the states (Abrams et al, 1999), using the amount of dollars in bank deposits, which is available from the FDIC's Summary of Deposit series after 1966. For prior years, we spliced in Call Report data for domestic deposits. An alternative interpretation of this variable is that it is a proxy for a state's private capital stock. Disintermediation has certainly lessened the importance of banks over the years, but as long as the effect is similar across all the states, then this measure will still be a good proxy.

We capture economic dynamism (Montgomery and Washer, 1988) with a measure of business failure rates: the number of failures in a year divided by the total number of business concerns in the state. The ultimate source for these data is the Statistical Abstract of the United States and the Metropolitan Area Databook.[5] Although we could not find a data source for startups over this lengthy period, in data from more recent eras, startups tend to be correlated with failures.

Industry Structure

We control for a state's previous economic makeup, specifically the composition of its sector specific capital and worker's human capital because the desirability of different industries may have changed, yet states can not adjust their industry make-up instantaneously, or without cost. Industry structure is measured as the shares of a state's personal income derived from manufacturing, farming, and mining, respectively. Implicitly, a state low in all of these industry structure variables will have a relatively large service sector.

Climate

[5]This variable required a fair amount of splicing and interpolation (contact authors for more details).

We also control for a state's meteorological climate as measured by heating-degree days, cooling-degree days, and inches of precipitation, using data available from the National Oceanic and Atmospheric Administration. Because they are annual averages from 1929 to 2003, they are constant over time.

Table 1 presents the values of per capita personal income and the various explanatory variables for the first and last observations for each state (1939 and 2004 data for personal income and 1934 and 1999 data, because of the lag, for the explanatory variables). One thing is very clear from Table 1: there is a wide range of variation in most of these variables across states even though they tend to follow the same general trends.

Figure 1(a) plots the course of the standard deviation of our dependent variable (the natural log of real per capita personal income) from 1934 to 2004. These standard deviations are a measure of how much per capita personal income varies across states in each year. After a slight downward trend in the late 1930s, there was a rapid surge towards convergence during World War II (WWII). Following the end of the war, convergence slowed but continued to decline at a steady pace through the late 1970s. Since 1970, convergence has basically leveled off.

Figures 1(b-d) are similar plots for the explanatory variables. The convergence in high school attainment (high school+) has been remarkable, falling about 80 percent. In contrast, there has been almost no convergence in college attainment (college+). For patents, our other knowledge variable, the spread across states narrowed about 25 percent over this period. Delaware is the only positive outlier for the patents variable, and no state is a negative outlier.

Our business-failure rate is fairly volatile over time. However, it shows no more tendency toward convergence than do our variables for tax rate, highway capital, or bank deposits. Interestingly, the variable with the smallest standard deviations over time is the tax rate variable, which has been fairly stable over the last 30 years.

There has been more movement in the industry-structure measures. Manufacturing's standard deviation has fallen by about a third over this period. Although historically there have been many large outliers for manufacturing, at present, no state deviates from the mean by more than 2 standard deviations. Mining's standard deviation, on the other hand, has only narrowed by about an eighth. West Virginia had been a big positive outlier in mining through the mid-1970s, but is no longer one. Only Wyoming is currently more than 2 standard deviations above the mean. In sharp contrast to the other two measures of industry structure, farming's standard deviation has actually diverged by about a fifth. The positive outliers with this variable are Nebraska, North Dakota, and South Dakota. Large negative outliers are Massachusetts, Rhode Island, and West Virginia.

IV. Baseline Estimates and Robustness Checks

Endogeneity and Lags

Contemporaneous observations of the explanatory variables are likely to be endogenous, so employing them would lead to biased and inconsistent estimates. Using instrumental variables can provide consistent estimates of the model's parameters, and lagged values make good instruments. But how long should the lag be? A longer lag makes it more likely that the possible endogeneity is removed but lowers the correlation between the lag and the instrumented variable. Also, assuming a longer lag effectively reduces the number of observations available for analysis.

Intuition suggests a 5-year lag is a reasonable value to balance these trade-offs, an assumption we test, using the Durbin-Wu-Hausman (D-W-H) test (see Baum, Schaffer, and Stillman, 2003). The test compares an estimator that is consistent, whether or not the subset of variables is predetermined, with an estimator that is consistent and more statistically efficient only if the set of variables is predetermined.

Table 2 reports D-W-H test results for various lag lengths for the regressors taken as a group and then for each one individually. For our always-consistent estimator, we employ 10-year lags as instruments. The other estimator, which is consistent only if the subset of variables is predetermined, employs the specified lag. Note that as the lag length varies, the data employed to calculate the tests change for two reasons. First, changing the lag length necessarily shifts the associations among the variables. The second reason is more subtle: increasing the lag length trims the number of observations, whereas trimming the lag length increases the number of observations.

With lag lengths less than 5 years, the null hypotheses that the variables are predetermined are soundly rejected at the 5 percent confidence level. For 5-year lags, the null is accepted for the joint test and for each explanatory variable individually—although this is a very close call with the tax-rate variable. While a 6-year lag is even less significant under the joint test, the individual tests for patents and tax rates are both rejected. Thus, when seeking a balance between handling endogeneity with sample size, we find that a 5-year lag is the best choice.

Baseline Results

Our baseline estimates, calculated from a panel OLS estimator, are reported in Table 3, column 1. Conventional measures of model fit are high enough to be irrelevant ($R^2 = 0.9983$), primarily due to the importance of the time dummies and the lagged dependent variables in fitting the level of incomes. A more informative measure of the goodness of fit is how much of 2004's *relative* personal per capita incomes are explained by our posited growth factors. The correlation between the actual and fitted values is fairly high (0.78), suggesting that the model explains about 78 percent of this variation.

Figure 2(a) shows the standard deviation of the predicted and actual log per capita income levels. Although the high R^2 does not convert into perfect predictions of the path of income convergence, the fit is quite good, except for the initial sharp decline in income differences during World War II, which is under-predicted in the model: Wartime mobilization (e.g. all privates are paid the same no matter which state they came from) appears to have accelerated income convergence.

Some understanding of the determinants of income growth can be gained by looking at the estimated parameters. The estimated coefficient on lagged logged per capita income is less than one (0.67). Because state per capita personal income is measured relative to the national trend, a value less than one implies convergence. Other things equal, this rate of convergence would halve the standard deviation of per capita incomes in just 10 years. In the model with no other explanatory variables than the time dummies, the coefficient on lagged per capita personal income is estimated to be 0.85, more than doubling the estimated number of years needed to achieve similar levels of convergence.

Implicitly, the difference in the coefficient on lagged per capita personal income between the two models (one with all the explanatory variables and the other with only the lagged dependent variable and the time dummies) reveals that state-level differences in the *X* variables have significantly reduced the amount of income convergence that has been realized, even though most of these variables have experienced some convergence across states as well.

Knowledge and Technology

All of the coefficients of the knowledge variables (high school+, college+, and patent stocks) have the expected sign and are statistically significant. Other things being equal, being one standard deviation above the states' average in the percentage of the population that has graduated from high school (a 20 percentage point increase) leads to 1.5 percent higher per capita personal income. Thus, the sharp rise of high school attainment in the sample is estimated to account for a sizeable portion of the income gains. However, further progress from this source is likely to be limited because high school attainment for these states averaged 83.3 percent in 1999 and its variance across states has diminished over time, see Figure 1(b).

Other things being equal, a one–standard-deviation increase above the states' average in the percentage of the population that has graduated from college (23 percentage points higher) leads to 1.4 percent higher per capita personal income. There is more room for improvement in college attainment than high school attainment: The states' average of this rate stood at 25.2 percent in 1999, and the rates of individual states vary from a low of 17.3 percent (Arkansas) to a high of 38.7 percent (Colorado).

Other things being equal, a one-standard-deviation increase above the states' average in the stock of patents per capita (75 percentage points higher) leads to 3.0 percent higher per capita personal income. This is a large effect, and it is also relatively tightly estimated with a t-statistic of over 6. While the spread of the patent variable has narrowed by about half over time, from a factor of about 30 in 1934 to about 15 in 1999, the range is still very wide.

Figure 2(b-c) compares the implied effects of the variables on the standard deviations in the baseline model. Each line is the standard deviation of the predicted effect for the indicated variable. For comparative purposes, the figures also include the standard deviation of predictions when all of the X variables are used in the model (but not the lagged dependent variable or time dummies). These estimates can either offset or amplify one another.

Industry Structure

Of the industry-structure variables, only manufacturing and farming's are ever statistically significant (see Table 3, column 1). The share of personal income derived from manufacturing has the clearest effect on relative per capita income—lowering expected current income levels relative to past income levels. Although income levels are relatively high in states that specialize in manufacturing at the start of the sample, these states either shift out of manufacturing or experience relatively weak income gains. Indeed, having a one-standard-deviation-higher share of manufacturing income (a 58 percent higher share than the states' average) lowers expected income growth by 2 percent, which is, again, an important difference.

Mining is also a statistically significant and negative factor, although its coefficient is far smaller. A one-standard-deviation increase in the mining share (a 142 percent larger share of income derived from mining than the states' average) lowers average income 1.1 percent. Farming is an insignificant factor, which might be surprising, given the steady decline in employment seen in this sector.

Figure 2(c) reveals that for explaining income differences, only the manufacturing effect has anywhere near the magnitude of the knowledge variables, and then it is only about the size of the educational attainment variables. Over time, as manufacturing levels have converged across states, the manufacturing effect explains less of the variation in income levels. The effect of mining on income differences is much smaller and is relatively unchanged over time. Farming has essentially no effect.

Climate

By design, the climate variables are constant over time. We find a statistically significant relationship for the cooling days and precipitation variables. States with a one-standard-deviation increase in log cooling days relative to the nation (about a 75 percent increase) have 1 percent higher income. Similarly, those with a one–standard-deviation-lower rate of precipitation (about a 50 percent reduction) have about 1 percent higher income.

Public Finance and Business Environment

The public finance variables do not have much explanatory power. The coefficient on highway capital, our proxy for public capital, is small and not statistically significant. Even if the coefficient were doubled, the effect of a one-standard-deviation increase in relative infrastructure spending would still be less than one-half of a percentage point. The story is similar for our tax variable. Its coefficient is also small and statistically insignificant. Again, its effect would remain small even if its coefficient were doubled.

Our business-environment variables also add little explanatory power. The coefficient on the failure rate of businesses, our measure of dynamism, is positive as anticipated, but not statistically significant. It also accounts for only a very small amount of the standard deviation in the dependent variable. Finally, the story for the bank-deposits variable, our proxy for private capital and the size of a state's financial markets, is again similar. Its coefficient is small and statistically insignificant, as is its estimated standard deviation.

Explanatory Variables and Interstate Income Differences

Each of our explanatory variables could either increase or decrease income differences across states, depending on the correlation between the effect of the variable and income levels in the states. In order to assess the effects of the statistically significant variables, we perform a series of counterfactual experiments, each of which involves setting a different set of explanatory variables to zero. Rerunning the regression then allows us to calculate the fraction of the variation in state incomes which the set of variables set to zero explains.

In Figure 2(d) we plot the resulting shares of variation explained by the major effects. The patents variable consistently explains the largest share of the standard deviations in our dependent variable. The next-largest share is the combined effect of the educational attainment variables (high school+ and college+). The gradual decline in the importance of the education variables is a result of the declining differences in high school attainment across states discussed earlier.

The other explanatory variables account for relatively small shares of the explained variation across states. The magnitudes of the effects of the industry-structure variables are smaller, but they have increased over time. Of these variables, the manufacturing variable has the largest role. As its coefficient is negative, a greater share of manufacturing can be interpreted as exerting a drag on state per capita personal income. Given the high incomes in manufacturing states in the 1940s, the effect of this factor has been to reduce income levels below what would have been. However, since the early 1970s, manufacturing intensity has been essentially uncorrelated with income.

Of the climate variables, both the cooling and precipitation variables are statistically significant. Both have a positive effect on per capita personal income. Even so, the magnitudes of the estimated effects of these variables are small.

Estimating the Model under Alternative Assumptions

Controlling for Possible Fixed Effects

While we have made every effort to include all the relevant explanatory variables, there are certainly some we would have liked to have included but could not because the data were not available. If these omitted variables matter and are also correlated with our included variables, then our baseline results would be inconsistent estimates of the coefficients. To explore the potential for the adverse effects of omitted variables, we use a fixed effects panel estimator, which can consistently estimate the time-varying regressors even when there are omitted time-invariant regressors.

The fixed-effect-parameter estimates are reported in the second column of Table 3. (By design, this estimator strips out any unobserved time-constant variables. A consequence is that any known time-invariant variables (in our case, the weather variables) are also removed.) The state fixed effects coefficients are jointly statistically significant at the 1 percent confidence level even though none of the individual state dummy coefficients is (even at the 5 percent confidence level). The estimates of the remaining variables do differ some from the baseline estimates. In particular, the magnitudes of the estimated coefficients of the knowledge variables all increase and remain statistically significant.[6] For the other explanatory variables, the results change very little, with only manufacturing's share of personal income losing its statistical significance.

Figure 3(a) illustrates the share of the standard deviation of per capita personal income explained by the fixed effects results. The time paths of the various effects are largely unchanged. The main observable shift from Figure 2(d) (aside from the flat-lined climate effect) is that the effect of patents is a bit lower over time. The effect of industry structure is also more muted. In short, allowing for fixed effects does not materially alter our story, suggesting that our results are not an artifact of omitted variable bias.

Allowing the Coefficients to Vary over Time

Our next perturbation of the model allows the coefficients of the explanatory variables to vary over time. Over a period this long, it could be argued that the underlying parameters have changed, either due to changes in technology or changes in

[6] If dummies for the four Census regions (Northeast, Midwest, South, and West) are included instead of the state fixed effects, their coefficients turn out to be statistically insignificant from zero. These coefficients become statistically significant if the climate variables are also omitted from the regression. Again,, the estimated effects are essentially unchanged.

political institutions. In order to determine if our results are sensitive to these underlying parameter changes, we estimate a version of the model that allows the parameters to vary over three periods within our sample, 1939 to1959, 1964 to 1979, and 1984 to 2004. With our 5-year lag, the first and last periods each have 5 cross sections while the second has only four. In this version of the model, to hold the dynamic structure of the model constant, we do not allow the coefficient of the lagged dependent variable to vary over time.

The parameter estimates of this model are presented in Table 3, columns 3 to 5. This permutation yields some larger changes. The patent effect becomes more important, at least in the early years of the sample. While the coefficient of the patents variable is statistically significant in all three periods, its magnitude in the earliest period, 0.0749, is twice as large as it is in the two latter periods, 0.0415 and 0.0376, and is only slightly lower than the baseline model's 0.0404. However, an F-test for whether these coefficients are all equal cannot be rejected at the 95 percent confidence level (p-value 0.0556). While the value of the average patent is likely to vary some over time, because our regressor is a function of a state's stock of patents per capita relative to the states overall average, trend toward making patents easier to obtain is unlikely to be the source of the variation in the patent variable's effects over time. Allowing the coefficients to vary over time shifted the education variables even more. The college+ variable (0.0577 in the baseline model) ranged from 0.0275 in the middle period to 0.0753 in the last period—the only period in which the variable was statistically significant. Not surprisingly given the relatively large standard errors, an F-test cannot reject the null hypothesis that the coefficients are the same in all three periods.

The high school+ variable (0.0781 in the baseline model) also dipped from 0.0671 in the first period to 0.0241 in the middle period, but rebounded to 0.0739 in the last period. Note that it was not statistically significant in any of the periods, and again the null hypothesis that the three coefficients are the same cannot be rejected. The magnitudes of these coefficients are similar to those in the baseline model, but their statistical precision is adversely affected by having fewer time series observations with which to estimate them.

The tax-rate variable, the business-failure-rate variable, and the banking-deposits variable, like their baseline counterparts, are all statistically insignificant. In contrast, our highway-capital variable is statistically significant in the first period, but not in the latter two. Even so, the magnitude for this variable remains fairly small even in the period in which it is significant.

Among the industry-structure variables, manufacturing's share of personal income remains a negative influence in all three time periods, but is statistically significant in only the first and last periods. The magnitude ranges from -0.0228 to -0.0339, roughly the same as the baseline model's magnitude of -0.034. Mining's share also is estimated to exert a negative influence, the same as in the baseline model. Finally, the coefficient on farming's share remained essentially zero.

The parameter estimates of the climate variables appear to suffer from the same lack of statistical precision that the education variables do. The magnitude of the parameters is essentially the same, but the coefficient estimates are not statistically significant.

The effects of the time-varying-parameter estimates are plotted in Figure 3(b). The main observable shift from Figure 2(d) is that the effect of patents is now estimated to decline over time. The major part of this decline is due to the fact that patents explain a much larger share of the standard deviation at the beginning of the sample. Another change is that the share of the standard deviation explained by education is a bit flatter over time in the time-varying parameter model than in the baseline model. A big change from the baseline results (Figure 2(d)) is that the effect of industry structure is now slightly larger in magnitude than the education variables. Finally, the climate variables explain a relatively small share of the standard deviation, as in the baseline results. In short, this robustness test reveals that the factors driving a state's per capita personal income remain largely unchanged, although the statistical precision suffers.

Varying the Lag Length

Another way to test the robustness of our findings is to vary the lag length. Qualitatively, our results remain the same whether the lag length is shortened to one or stretched to 20. The sixth column of Table 3 reports the parameter estimates when the lag length is set to 10 (other results can be obtained from the authors). The main change is that the coefficients for the knowledge variables are both larger in magnitude and statistical significance than in the baseline model. Once again, although there is some shift in the magnitude and trends, patents and educational attainment are still the main drivers of state per capita personal incomes (see Figure 3(c)).

Varying Rates of Depreciation

A final set of robustness tests varied the rate of depreciation used in constructing the patents and highway capital stock measures. The results are also robust to this variation. Even increasing the depreciation rate to 100 percent, effectively turning these stock variables into flows, yielded largely the same parameter estimates (see last column of table 3). The estimated coefficient for high school attainment is somewhat higher, while those for college attainment and patents are slightly lower. As in the other permutations, the main four categories still explain most of the variation across states, and their respective magnitudes are on the same scale. The knowledge variables still explain the bulk of the variation in per capita personal incomes across states (see Figure 3(d)). The main visible change is that in the 1950s, the education effect briefly is larger than the patent effect.

Looking at the results more closely, note that setting the depreciation rate to 100 percent means that the patent variable contains only one (lagged) period's information, effectively discarding all the prior years' information. This version of the patent variable still explains the largest share of the variation in states' per capita personal incomes, about 40 percent, but the baseline model's definition (with 5 percent depreciation) accounts for about 60 percent. Clearly, treating the patents as a stock variable improves the model's performance.

V. A Closer Look at States

Figures 4(a-b) show how much state per capita personal incomes have converged. Much of the convergence comes from states at the lower end of the distribution moving up toward the average. In 1939, states ranged from less than -0.8 log point to more than 0.6 log point away from the overall average. In sharp contrast, the range for 2004 was only from a little less than -0.2 to under 0.4. Also, while some states have improved their relative position and some have lost ground, there appears to be a great deal of persistence in relative per capita personal incomes. This persistence makes it much less likely that the remaining wide range of outcomes is due primarily to random shocks.

The full impact of the explanatory variables over time is best captured by a cumulative effect because previous values exert an indirect effect through the lagged value of per capita personal income. For example, a high level of the educational attainment regressor in one period not only leads to a higher level of per capita personal income in that period, but some of it is propagated into future periods through the lagged coefficient. An explanatory variable's total effect on per capita personal incomes at the end of the period can be estimated as,

$$total\_effect = \sum_{t=1}^{T} \left(\hat{\beta}_x x_t\right) \hat{\beta}_1^{\,T-t} \tag{6}$$

Note that because the lagged coefficient on per capita income ($\hat{\beta}_1$) is less than one (see Table 3), a given x_t has a diminishing effect on future per capita personal incomes the further into the future one goes.

The estimated cumulative effects for our baseline and fixed effects estimators are plotted in Figures 5(a-b). In 2004, the estimated cumulative effects account for about half of the differences across states on average in relative per capita personal incomes.

VI. Conclusion

Neoclassical growth theory suggests that the per capita personal income of residents of the U.S. states should converge over time given the absence of barriers to the flow of information, labor, and capital across state boundaries. However, as Figure 1(a) illustrates, convergence of per capita personal income levels across U.S. states is not complete, and appears to have stalled since the mid 1970s. This observation led us to look for factors that could account for a lack of convergence. We did this constructing a Romer-type endogenous growth model by taking a standard Solow growth model and introducing state-specific labor-augmenting factors in order to control for the underlying convergence process. We found that a state's productive stock of knowledge appears to enhance its relative level of per capita income.

We control for classes of variables that previous researchers have argued influence relative per capita income levels across states: tax burdens, public infrastructure, size of private financial markets, rates of business failure, industry structure, and climate. We find that our three measures of a state's knowledge stock (the proportion of the population with at least a high school degree, the proportion of the state's population with at least a bachelor's degree, and the stock of patents held by people or businesses in the state) matter the most. We find that these effects are robust to a wide variety of perturbations to the model. Other things equal, being one standard deviation above the states' average in the stock of patents per capita (75 percent higher) leads to 3.0 percent higher per capita personal income. Similarly, being one standard deviation above the states' average in high school attainment (a 20 percentage point increase) leads to 1.5 percent higher per capita personal income. Finally, being one standard deviation above the states' average in college attainment (23 percentage points higher) leads to 1.4 percent higher per capita personal income.

In short, we find that incomes have failed to converge because knowledge stocks have failed to converge. If state policymakers want to improve their state's economic performance, then they should concentrate on effective ways of boosting their stock of knowledge. Of course, further research will be needed to determine the most efficient way of accomplishing this.

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Figure 1: Standard Deviations of Variables

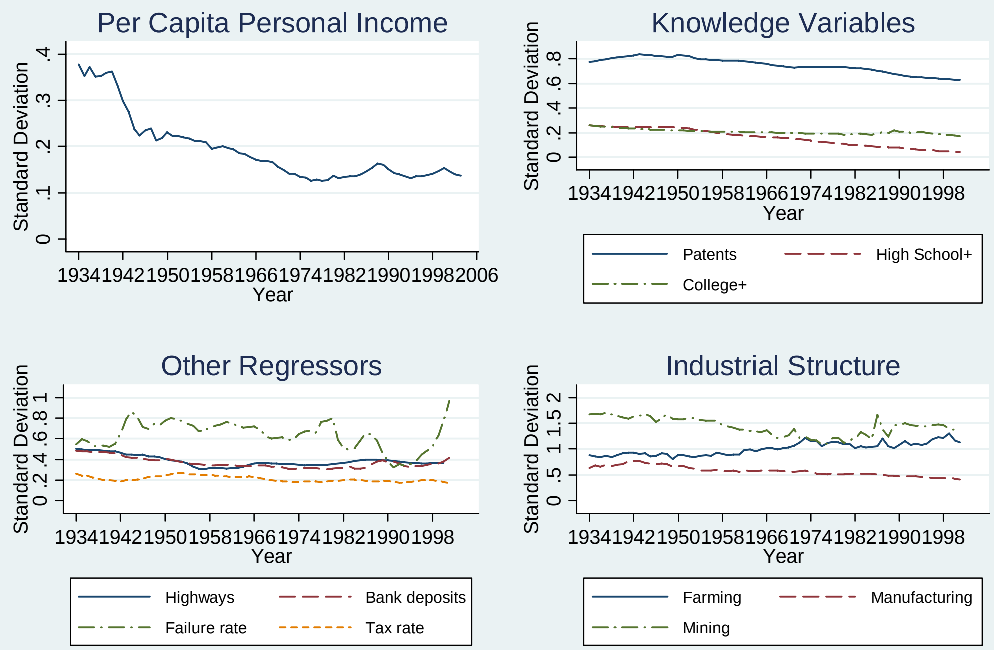

Figure 2: Baseline Model Performance

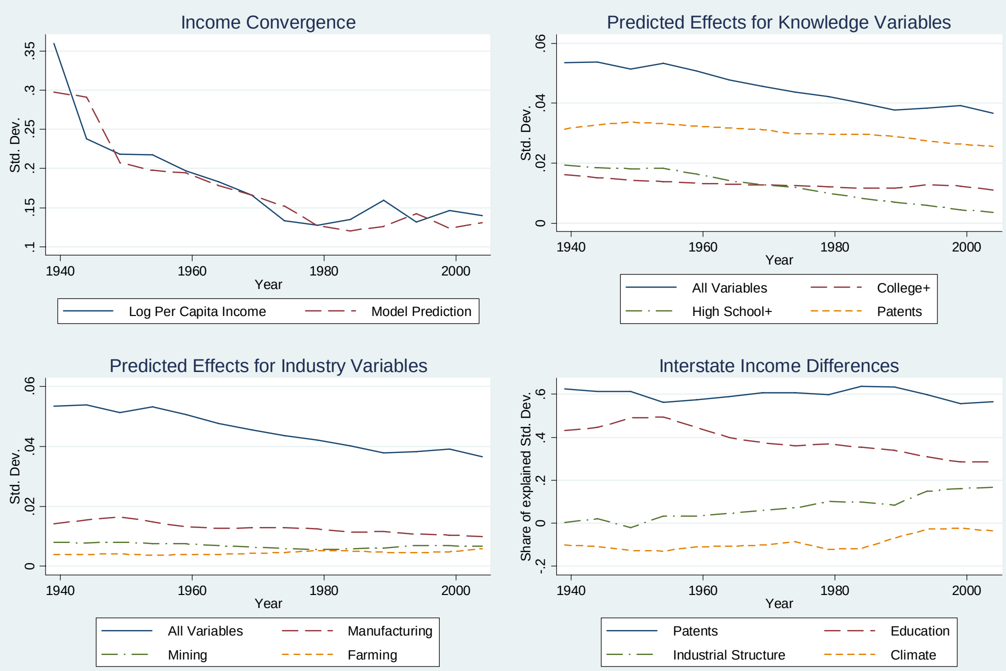

Figure 3: Exploring Robustness

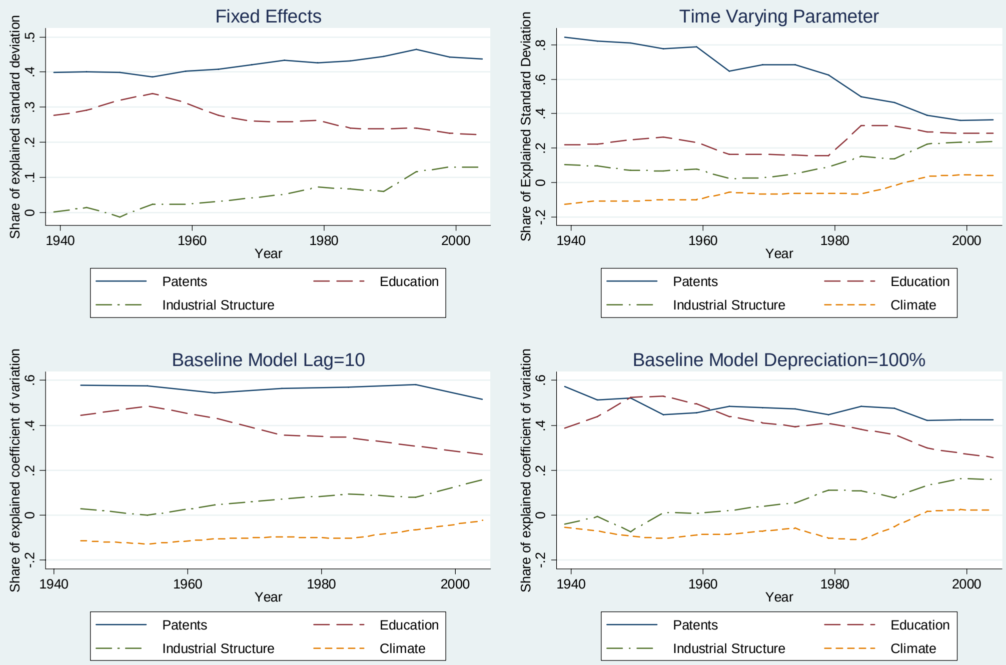

Figure 4: State Relative Incomes

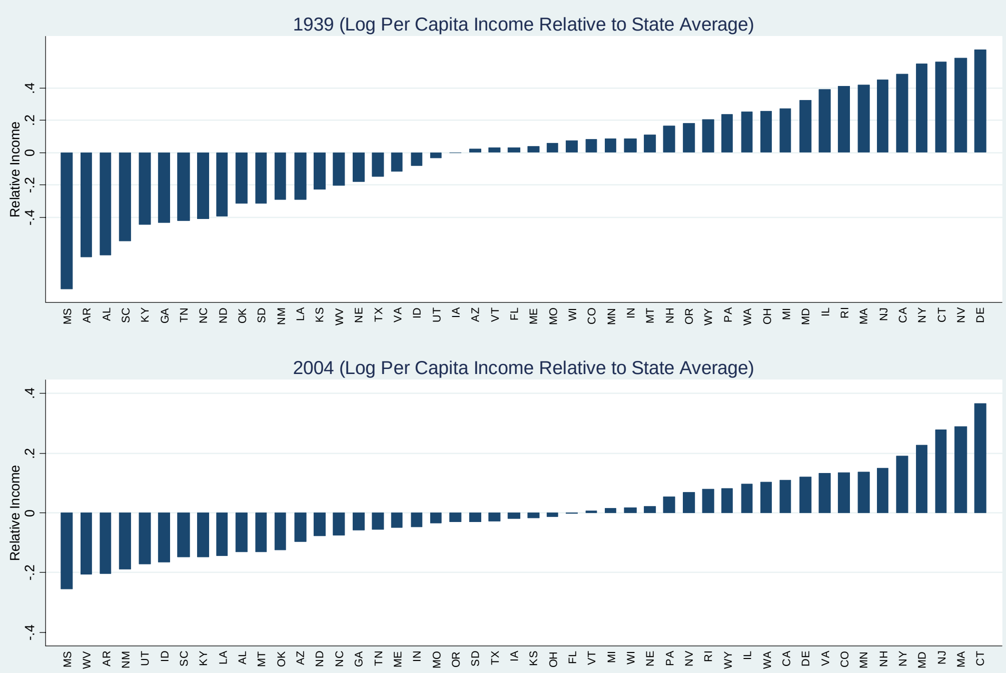

Figure 5: Cumulative Effects of Explanatory Variables

Table 1: Values of Selected Variables

State	Population (000)		Personal Income (real per capita)		Patents (per capita)		High School+ (percent)		College+ (percent)	
	1934	1999	1934	2005	1934	1999	1934	1999	1934	1999
Alabama	2,685	4,430	2,220	25,352	0.053	0.091	13.1	81.1	2.5	21.8
Arizona	428	5,024	3,789	26,241	0.114	0.298	24.8	83.1	5.7	24.2
Arkansas	1,878	2,652	1,953	23,602	0.024	0.071	12.1	78.9	1.8	17.3
California	6,060	33,499	6,254	32,285	0.440	0.501	34.7	80.4	8.5	27.1
Colorado	1,075	4,226	3,874	33,095	0.224	0.429	26.5	90.4	4.9	38.7
Connecticut	1,650	3,386	6,862	41,766	0.818	0.530	19.4	83.7	3.9	33.5
Delaware	250	775	6,798	32,605	0.848	0.538	18.7	84.5	4.2	24.0
Florida	1,585	15,759	3,629	28,855	0.146	0.165	22.0	82.7	4.2	21.6
Georgia	2,964	8,046	2,561	27,292	0.048	0.164	15.6	80.7	2.8	21.5
Idaho	473	1,276	4,237	24,567	0.070	0.959	25.3	84.8	3.9	20.8
Illinois	7,772	12,359	5,304	31,833	0.559	0.302	19.6	85.4	3.8	25.6
Indiana	3,319	6,045	3,778	27,611	0.367	0.238	19.7	82.9	3.1	18.4
Iowa	2,510	2,918	2,828	28,402	0.148	0.255	24.2	89.7	3.7	21.7
Kansas	1,868	2,678	2,999	28,436	0.094	0.162	23.1	87.6	3.8	26.5
Kentucky	2,722	4,018	2,455	24,911	0.061	0.113	12.6	78.2	2.5	19.8
Louisiana	2,202	4,461	2,764	24,999	0.047	0.108	15.5	78.3	2.9	20.7
Maine	829	1,267	4,376	27,520	0.107	0.096	24.4	88.9	2.6	22.9
Maryland	1,710	5,255	5,443	36,303	0.291	0.287	16.1	84.7	3.8	34.7
Massachusetts	4,305	6,317	6,414	38,645	0.519	0.557	25.2	85.1	4.6	31.0
Michigan	4,798	9,897	4,760	29,404	0.478	0.372	20.1	85.5	3.4	21.3
Minnesota	2,695	4,873	3,767	33,184	0.210	0.544	20.3	91.1	3.5	32.0
Mississippi	2,050	2,828	1,825	22,362	0.015	0.066	9.6	78.0	2.6	19.2
Missouri	3,784	5,562	3,863	27,948	0.230	0.167	18.3	85.0	3.4	23.0
Montana	545	898	3,831	25,357	0.090	0.140	24.5	88.8	4.2	24.0
Nebraska	1,382	1,705	2,721	29,576	0.101	0.112	24.0	89.3	3.8	20.4
Nevada	98	1,935	5,688	30,990	0.133	0.152	29.1	86.4	6.0	20.2
New Hampshire	480	1,222	5,005	33,626	0.304	0.533	22.0	86.5	3.5	27.2
New Jersey	4,089	8,360	6,019	38,224	0.778	0.477	17.6	87.4	4.2	30.5
New Mexico	461	1,808	2,593	23,976	0.037	0.187	18.6	80.9	3.5	24.5

Table 1: Values of Selected Variables (continued)

State	Population (000)		Personal Income (real per capita)		Patents (per capita)		High School+ (percent)		College+ (percent)	
	1934	1999	1934	2005	1934	1999	1934	1999	1934	1999
New York	13,253	18,883	7,129	35,039	0.581	0.324	17.8	81.9	4.6	26.9
North Carolina	3,304	7,949	2,657	26,862	0.044	0.218	17.7	79.8	3.6	23.9
North Dakota	672	644	1,910	26,726	0.046	0.104	18.5	84.9	3.0	22.3
Ohio	6,751	11,335	4,781	28,560	0.558	0.296	20.8	86.1	3.8	25.5
Oklahoma	2,391	3,437	2,625	25,498	0.102	0.144	20.1	83.5	4.0	23.7
Oregon	985	3,394	4,621	28,058	0.214	0.323	28.1	86.2	4.8	26.8
Pennsylvania	9,795	12,264	5,069	30,512	0.357	0.306	16.5	86.1	3.6	23.9
Rhode Island	675	1,040	6,297	31,350	0.410	0.251	16.5	80.9	3.8	26.8
South Carolina	1,760	3,975	2,209	24,889	0.026	0.141	17.9	78.6	4.3	20.9
South Dakota	682	750	1,942	28,073	0.067	0.088	20.5	88.7	3.2	25.6
Tennessee	2,784	5,639	2,572	27,356	0.078	0.152	14.9	79.1	2.6	17.7
Texas	6,053	20,558	3,042	28,160	0.099	0.294	21.7	78.2	3.7	24.4
Utah	522	2,203	3,266	24,376	0.121	0.308	30.8	91.0	5.4	27.9
Vermont	357	605	4,013	29,098	0.157	0.562	23.2	89.3	3.4	28.3
Virginia	2,485	7,000	3,340	33,063	0.093	0.149	18.0	87.3	3.6	31.6
Washington	1,610	5,843	4,642	32,080	0.232	0.313	28.3	91.2	4.7	28.6
West Virginia	1,771	1,812	3,298	23,575	0.088	0.082	14.4	75.1	2.9	17.9
Wisconsin	3,054	5,333	3,991	29,418	0.383	0.314	17.3	86.8	3.2	23.6
Wyoming	233	492	4,290	31,386	0.150	0.106	27.9	90.7	4.2	22.3
Average	2,621	5,763	3,965	29,230	0.233	0.273	20.6	84.5	3.8	24.6

*The GDP price deflator, base year=2000, was used to calculate real values.

Table 1 (continued)

State	Tax Rate (proportion)		Highway Capital (real per capita)		Business Failure Rate (proportion)		Bank Deposits (real per capita)	
	1934	1999	1934	1999	1934	1999	1934	1999
Alabama	0.0474	0.0594	655	1,387	0.00335	0.00416	9,690	11,800
Arizona	0.0721	0.0624	1,070	1,373	0.00102	0.00835	42,625	7,666
Arkansas	0.0606	0.0820	2,139	1,568	0.00335	0.00580	8,381	11,466
California	0.0365	0.0724	399	606	0.01002	0.01232	43,235	9,051
Colorado	0.0473	0.0507	601	1,199	0.00523	0.00920	21,957	9,501
Connecticut	0.0334	0.0741	513	2,041	0.01017	0.00260	29,148	15,344
Delaware	0.0606	0.0906	1,317	2,868	0.00159	0.00091	33,401	68,013
Florida	0.0512	0.0560	665	1,320	0.00267	0.00240	39,266	11,043
Georgia	0.0431	0.0588	709	1,531	0.00300	0.00216	11,980	10,723
Idaho	0.0425	0.0745	742	1,912	0.00310	0.00489	14,768	7,289
Illinois	0.0255	0.0568	689	1,468	0.00566	0.00698	22,777	15,372
Indiana	0.0478	0.0629	438	1,342	0.00337	0.00133	16,581	10,032
Iowa	0.0645	0.0664	740	2,256	0.00331	0.00107	13,817	13,161
Kansas	0.0462	0.0647	1,680	2,156	0.00198	0.01042	13,996	11,628
Kentucky	0.0550	0.0785	442	2,318	0.00226	0.00128	10,080	11,627
Louisiana	0.0666	0.0625	853	1,863	0.00175	0.00386	15,686	9,586
Maine	0.0554	0.0819	824	1,444	0.00676	0.00316	13,376	10,102
Maryland	0.0328	0.0569	509	1,291	0.00606	0.00621	20,641	9,578
Massachusetts	0.0279	0.0681	252	1,962	0.00960	0.00324	25,733	20,174
Michigan	0.0493	0.0785	476	925	0.00393	0.00365	20,198	9,780
Minnesota	0.0526	0.0851	953	1,468	0.00459	0.01081	18,582	13,657
Mississippi	0.0480	0.0803	397	1,776	0.00343	0.00276	8,388	9,827
Missouri	0.0335	0.0599	1,112	1,442	0.00331	0.00552	15,740	12,751
Montana	0.0408	0.0656	824	3,299	0.00442	0.00552	15,456	8,923
Nebraska	0.0442	0.0590	811	2,352	0.00562	0.00400	12,749	14,638
Nevada	0.0552	0.0602	3,971	1,538	0.00261	0.01201	62,158	8,237
New Hampshire	0.0467	0.0288	407	1,332	0.00324	0.00451	26,508	15,034
New Jersey	0.0381	0.0575	908	1,674	0.00956	0.00434	19,924	14,244
New Mexico	0.0665	0.0837	1,142	1,868	0.00146	0.00759	17,588	6,929

Table 1 (continued)

State	Tax Rate (proportion)		Highway Capital (real per capita)		Business Failure Rate (proportion)		Bank Deposits (real per capita)	
	1934	1999	1934	1999	1934	1999	1934	1999
New York	0.0303	0.0625	365	1,302	0.01188	0.00520	46,101	20,627
North Carolina	0.0582	0.0710	473	1,403	0.00364	0.00310	10,050	12,719
North Dakota	0.0600	0.0674	442	2,767	0.00150	0.00581	12,448	14,570
Ohio	0.0335	0.0597	253	1,295	0.00571	0.00595	14,735	11,534
Oklahoma	0.0579	0.0671	887	1,554	0.00350	0.00580	13,024	9,721
Oregon	0.0528	0.0589	1,138	1,381	0.01012	0.00771	21,993	7,793
Pennsylvania	0.0392	0.0630	352	1,196	0.00415	0.00535	16,667	12,946
Rhode Island	0.0312	0.0663	550	1,937	0.01356	0.00274	27,278	11,930
South Carolina	0.0588	0.0672	874	1,145	0.00246	0.00359	6,503	7,742
South Dakota	0.0838	0.0472	850	3,001	0.00214	0.01011	11,897	15,727
Tennessee	0.0445	0.0513	1,133	1,701	0.00473	0.00497	13,483	11,784
Texas	0.0533	0.0463	933	1,359	0.00263	0.00733	23,024	9,064
Utah	0.0708	0.0738	673	1,908	0.00809	0.00271	19,917	8,632
Vermont	0.0665	0.0887	1,893	1,600	0.00342	0.00156	16,786	11,549
Virginia	0.0464	0.0565	894	1,807	0.00517	0.00396	15,261	10,522
Washington	0.0538	0.0699	805	1,520	0.00784	0.00695	23,265	9,218
West Virginia	0.0496	0.0838	607	2,968	0.00656	0.00558	8,791	11,414
Wisconsin	0.0513	0.0803	918	1,108	0.00539	0.00501	15,475	12,454
Wyoming	0.0520	0.0474	2,326	5,655	0.00327	0.00719	19,695	12,861
Average	0.0497	0.0660	888	1,796	0.00484	0.00524	20,017	12,708

*The GDP price deflator, base year=2000, was used to calculate real values.

Table 2: Endogeneity Tests

Lag	All	Stock of Patents	Educational Attainments	Business Failure Rate	Tax Rate	Highway Capital	Banking Deposits
1	0.000	0.000	0.000	0.000	0.000	0.076	0.000
2	0.000	**0.331**	0.002	0.000	0.000	**0.330**	0.007
3	0.000	**0.621**	0.000	0.005	0.001	**0.205**	**0.458**
4	0.002	0.009	**0.297**	0.034	0.003	**0.734**	**0.112**
5	**0.149**	**0.583**	**0.181**	**0.118**	**0.145**	**0.553**	**0.121**
6	**0.369**	0.041	**0.779**	**0.341**	0.765	**0.940**	**0.540**
7	**0.161**	**0.141**	**0.057**	**0.390**	**0.799**	**0.819**	**0.371**
8	**0.768**	**0.899**	**0.735**	**0.150**	**0.991**	**0.699**	**0.180**

Table 3: Regression results

	Baseline Lag=5	Fixed Effect Lag=5	Time Varying Parameters 1939-1959	1964-1979	1984-2004	Baseline Lag=10	Baseline 100% Depreciation
Lagged Income	0.673	0.557	0.630	0.630	0.630	0.434	0.665
	(31.06)**	(21.43)**	(25.35)**	(25.35)**	(25.35)**	(13.29)**	(28.95)**
Manufacturing Share	-0.0224	0.0110	-0.00573	-0.0214	-0.0344	-0.0336	-0.0312
	(-3.21)**	(0.91)	(-0.57)	(-1.47)	(-2.47)**	(-3.08)**	(-4.25)**
Farm Share	-0.00452	-0.00961	-0.0109	0.00269	-0.00638	-0.00896	-0.00566
	(-1.51)	(-1.68)	(-1.37)	(0.45)	(-1.57)	(-1.84)	(-1.91)
Mining Share	-0.00477	0.00744	-0.00173	-0.00965	-0.0108	-0.00731	-0.00392
	(-2.23)*	(1.37)	(-0.57)	(-2.10)*	(-2.48)*	(-2.20)*	(-1.84)*
Heating Days	0.00944	na	-0.0177	-0.00439	0.0202	0.0205	0.0248
	(1.01)		(-0.92)	(-0.24)	(1.42)	(1.36)	(2.84)**
Cooling Days	0.0135	na	0.0167	0.00831	0.107	0.0236	0.0140
	(2.33)*		(1.60)	(0.73)	(1.16)	(2.55)*	(2.43)*
Precipitation	0.201	na	-0.0143	-0.00679	0.0340	0.0323	0.0291
	(2.11)*		(-0.69)	(-0.33)	(2.27)*	(2.10)*	(3.01)**
High School+	0.0744	0.0824	0.0670	0.0244	0.0378	0.120	0.103
	(3.08)**	(2.31)*	(1.87)	(0.42)	(0.46)	(3.18)**	(4.26)**
College+	0.0624	0.109	0.0278	0.0264	0.0959	0.103	0.0497
	(3.61)**	(3.78)**	(0.83)	(0.78)	(3.19)**	(3.75)**	(2.80)**
Stock of Patents	0.0405	0.0560	0.0751	0.0417	0.0367	0.0619	0.0323
	(6.17)**	(4.39)**	(5.64)**	(3.37)**	(3.63)**	(5.88)**	(5.30)**
Business Failure Rate	0.00304	-0.00400	0.00259	0.0128	0.00567	0.00320	0.00112
	(0.76)	(-0.89)	(0.36)	(1.55)	(0.81)	(0.48)	(0.28)
Tax Rate	-0.0155	-0.0106	-0.0174	-0.0360	-0.0233	-0.0194	-0.0163
	(-1.35)	(-0.63)	(-0.86)	(-1.69)	(-1.13)	(-1.08)	(-1.42)
Highway Capital	0.00880	0.0215	0.0341	0.0137	-0.00915	0.00449	-0.00458
	(1.05)	(1.69)	(2.81)*	(0.71)	(-0.54)	(0.35)	(-0.74)
Banking Deposits	-0.00590	-0.0136	-0.0195	-0.00381	-0.00557	-0.00222	0.00739
	(-0.064)	(-0.98)	(-1.01)	(-0.19)	(-0.63)	(-0.15)	(0.83)
Observations	672	672		672		336	672
R-squared	0.998	0.998		0.998		0.998	0.998

Value of t statistics in parentheses
* significant at 5%; ** significant at 1%