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Real average U.S. per capita personal income growth over the last 65 years exceeded a remarkable 400 percent. Also notable over this period is that the stark income differences across states have narrowed considerably: In 1939 the highest income state's per capita personal income was 4.5 times the lowest, but by 1976 this ratio had fallen to less than 2 times. 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. A better understanding of the sources of these relative growth performances should help to characterize more effective economic development strategies, if income growth differences are predictable. In this paper, we look for statistically and economically significant growth factors by estimating an augmented growth model using 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 mid 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. Some researchers have focused on differences in tax policy (Easterly and Sergion, 1993; Mofidi and Stone, 1990; Phillips and Gross, 1990), others on varying rates of investment in public infrastructure (Aschauer, 1989; Evans and Karras, 1994; Wylie, 1996). Still others have argued that past industry structure may aid or inhibit future economic development (Higgins, Levy, and Young, 2006). For others, climate differences combined with the advent of affordable air conditioning play a prominent role (Barro and Sala-i-Martin, 1991). Other explanations center on financial markets and economic performance (Abrams et al., 1999; King and Levine, 1993; Levine, 1997; Montgomery and Wascher, 1988; Rousseau and Wachtel, 1998). Last, but certainly not least, many researchers have focused on knowledge and technology. Their explanation is based on the empirical observation that higher levels of per capita personal incomes are associated with greater knowledge stocks (Glaeser and Saiz, 2004). By knowledge stocks we mean the accumulation of productive information in the form of education and technology.

Because our results overwhelmingly support the knowledge-stock explanation, it is appropriate to review this literature more thoroughly. 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; (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).

Education and technology constitute much of states' knowledge stocks, and one might wonder why the greater levels of education and technology of some states does not dissipate to others, leading to a equalization of knowledge stocks. While some dissipation occurs, the diffusion across state borders is likely to be incomplete. Migration of people is costly, and not all people will migrate even when entities in other states pay higher wages for their education (Barro and Sala-i-Martin, 1991). Also, knowledge spillovers appear to decrease with distance, making it harder for entities in other states to fully imitate the technology developed in a state (Griliches, 1979). Furthermore, research shows very little evidence of externalities in human capital at the state level (Rangazas, 2005). Consequently, some portion of a state's knowledge stock will remain in that state, and the larger knowledge stocks of some states will enhance their relative level of per capita personal income (Barro and Sala-i-Martin, 1991).

In order to investigate the effect of knowledge stocks and the other possible explanatory variables on per capita personal income, it is important to embed them within a growth model that allows for the convergence in per capita incomes due to the relative freedom of movement in capital and labor across state borders. So we embed a variety of state-specific labor augmenting factors into a standard neoclassical growth model. This allows 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 1999. The longer time frame gives us greater statistical precision, allowing us to tease out the effects of factors that have weaker effects on relative per capita income growth, and that might have been obscured in previous studies.

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). By including variables that account for a wide range of alternative explanations, we can estimate the magnitude of the effect that investments in knowledge will have relative to investments in the other factors that affect income growth. We can also mitigate the imprecision of these estimates of investment effects that stems from omitted variable bias.

In a study as ambitious as this one, it is important to thoroughly explore the robustness of our findings. Of particular concern is the possible endogeneity of most of the explanatory variables. For example, a problem with many efforts to associate international differences in knowledge stocks and levels of per capita personal income is 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 consume more knowledge. As a result, knowledge stocks and per capita personal income could be positively correlated without knowledge stocks directly causing one state's per capita personal income to be higher than another's. We test for predetermination of the explanatory variables using instruments based on lags of differing duration and show that a five-year lag removes (statistically) the threat of endogeneity.

Under all perturbations, we find that the knowledge variables play the main role in accounting for relative levels of per capita income across states. Their magnitude and statistical significance dominate the other explanatory variables. Moreover, within the set of knowledge factors, we find that investments in technology, as measured by the stock of patents, play the largest role in explaining the differences in per capita personal incomes across states.

The paper proceeds as follows: The next section presents our modified growth model. The third section describes the data and the variables. The fourth section presents our results. The final section concludes.

II. Model

Growth theory strives to explain how an economy's output, investment, and employment evolves in the long run. Solow (1956) provided a major advance to the field by focusing the analysis on the production function associated with current technology. Along with diminishing marginal returns to capital, introducing capital mobility implies a strong underlying tendency for income convergence through capital equalization. A shortcoming of his approach is that technological innovation, the Solow residual, enters the model exogenously. Romer (1986) pointed out that the development of innovations usually requires some diversion of productive resources away from current consumption, indicating that technological innovation is endogenous.

We take Romer's (1986) critique of growth theory to heart by including in our model measurable factors that <u>might</u> enter into the aggregate production function of that state. These factors do not reveal the actual process of resource diversion but 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, we can do so with greater precision because we have a longer time period and we can control for more factors. The data available for U.S. states are richer than what is available internationally, allowing us to examine a wider set of factors.[2]

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

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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.

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.

In our baseline model, we also control for one factor that is not typically thought to be labor augmenting: climate. A favorable climate could be a local amenity that boosts productivity and thus incomes. Alternatively, a climate considered favorable by residents might make them willing to accept a lower income rather than relocate.

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,

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

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.)

[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.

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. 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:

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

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.

While we can learn several key aspects of the relevance of state-level regressors on income levels from the regression shown in equation (2), accounting for the correlation with the other variables in the model is necessary to estimate the effects of these explanatory variables on income convergence across states. In Barro and Sala-i-Martin (1991) terms, this evaluates the role of the variables in state-level σ convergence, when the dispersion of real per capita income across a group of economies falls over time. Taking the standard deviation of both sides of equation (2) and focusing on the *X* variables results in the following relationship,

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

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. Data

In this section we describe the data we collected to estimate our growth model, focusing on the motivation, source, and construction of the regressors we employ. 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. We also include explanatory variables that previous researchers have argued are important. The larger sample should increase the statistical precision of our results, enabling us to tease out even weak effects. Moreover, by including variables that account for all the proposed explanations, we should be able to sort out how much each factor drives state per capita personal income, and mitigate bias from omitted variables.

Collecting a data set like this is very challenging. Some of our variables go farther back than others, and the historical series for the variables vary by state. The banking data turned out to be the limiting factor in our data set, as deposit information by state 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, which means we have per capita personal income from that year, but for the lagged explanatory variables values are from 1999. Data availability also led us to consider only 48 contiguous states because data for Alaska, Hawaii, and the District of Columbia are incomplete. Because we omit the years in between the five-year periods in order to avoid artificially underestimating the standard errors,[4] we are left with a panel of 48 states over 14 five-year periods. Although this approach may seem drastic because it tosses away observations that could be retained if the time series properties of the errors were modeled explicitly, the approach has the advantage of being more flexible. In addition, because our educational attainment data are only available decennially from 1940 to 1980, (details to come), we are not really discarding as much information as it appears. Thus, our approach is appropriately conservative.

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*.

[4] We drop these observations to avoid having to model the time series properties of the residual.

We will now describe the set of regressors we employ to estimate the model. The first two types are mainly control variables—they are not the focus of our study, but they need to be included in order to obtain consistent estimates of the coefficients of the factors in which we are interested. First, we include a lagged dependent variable because equation (2) calls for it in order to capture the dynamic adjustment process. Second, we include year-time dummies, which capture the national movements in prices and also the average effects across states of movements in technology. They also pick up any other national trends that might be in the data.

We include a variety of 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.

As discussed earlier, we include several classes of variables that might influence a state's rate of convergence. A key class of variables we call knowledge variables. These variables seek to measure a state's stock of knowledge. Two of these variables measure educational attainment. The first is the proportion of a state's population with at least a high school degree The other is 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 (see Figure 2).

Our other knowledge variable is a state's stock of patents. This variable proxies for a state's ability to innovate new products and production techniques that could give it an economic edge and lead to higher relative per capita personal incomes. A state with a larger stock of patents is presumed to be more innovative in creating new products and production techniques. Patent data by state are 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 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—the way in which states raise and spend tax revenue—is widely thought to influence a state's economic performance, and it comprises another set of explanatory variables. Many analysts focus on tax rates (Mofidi and Stone, 1990; Phillips and Gross, 1995). Therefore, we include a measure of tax rates. Our tax rate variable is 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. 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.

Other researchers have argued that expenditures on public infrastructure are an important growth factor (Aschauer, 1990; Wylie, 1996). Thus, we include a measure of infrastructure expenditures. Our proxy for public capital, highway capital, is constructed using a perpetual-inventory approach. Our measure of highway spending comes 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.

Our last set of explanatory variables describes a state's business environment. Some researchers think that the extent of private financial markets within the states influences their economic performance (Abrams et al, 1999). Our measure of private financial markets within the states is based on 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.

Some analysts think that economic dynamism influences economic performance (Montgomery and Washer, 1988). We capture dynamism with a measure of business failure rates. Our failure-rate variable is the number of bankruptcies 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]

Over time, the desirability of different industries may have changed, yet states can not adjust their industry make-up instantaneously, or without cost. The industry structure factors control for a state's previous economic makeup, specifically the composition of its sector specific capital and worker's human capital. 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 serviced sector.

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

Some insight can be gained by looking at the raw variables. 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). Population grew in every state except North Dakota over this period, and every state experienced rapid growth in its per capita personal incomes. Among our knowledge-stock variables, both high school and college attainment have increased dramatically, while patents per capita have remained relatively flat. Some researchers have noted that the value of patents may have changed over time (see Griliches, 1990). Any inflation or deflation of the quality of

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

patents over time will be filtered out because the patent variable in the model is relative to the average of these states.

Among the other classes of explanatory variables, tax rates (tax revenue over personal income) rose over this period, but not as dramatically as highway capital. By contrast, failure rates rose slightly, but as we will see in a moment, this masks a great deal of volatility over time. Bank deposits actually fell substantially over this period because of disintermediation. Savers have many more options today over where to put their funds, such as money market accounts and mutual funds. 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.

Further insights can be gleaned by plotting the raw data. 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 incomes vary 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+). It is worth knowing how the levels of these variables have moved overall. Figure 2(a) plots the rise in high school and college attainment over time. Only about 20 percent of the population had at least a high school degree in 1934, but by the end of our sample, well over 80 percent had achieved this level of education. Gains in this variable have sharply leveled off in recent years. As for college education, in 1934 less than 4 percent of the population had at least a bachelor's degree, but, by 1999, this figure had risen to 25 percent. Unlike high school attainment, gains in college attainment, which accelerated around 1970, show no sign of easing. Currently, while there are no outliers for high school attainment (defined as more than two standard deviations from the mean), Arkansas and West Virginia are both negative outliers for college attainment.

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. In Figure 2(b), we see that per capita patents fell sharply during WWII but recovered in the late 1940s and held at the 1940s level through the mid-1970s. Since 1980, patents per capita have risen sharply and have accelerated since 1997.

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 a 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. Results

In this section we discuss our baseline estimates. We then explore how robust our estimates are to alternative assumptions. Finally, we take a closer look at the results by looking at state-specific estimates.

Endogeneity and Lags

The baseline model assumes that the parameters are fixed over time and that a 5-year lag is sufficient to handle any endogeneity of the explanatory variables. 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. We use the same lag length for the lag of the dependent variable, even though the motivation for this lag stems from the partial adjustment process.

The key to the instrumental-variable approach is to find instruments that are highly correlated with the regressors, yet are uncorrelated with the error term. Lagged values of the regressors are likely to meet both of these criteria, 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. Of course, this assumption needs to be tested, and we do this using the Durbin-Wu-Hausman (D-W-H) test (see Baum, Schaffer, and Stillman, 2003), which can be used to test whether a regressor, or subset of regressors, is endogenous. 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 estimator that 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 model with only these variables generates an R^2 of 0.9976. 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.

From the perspective of state income differences, a more informative comparison can be made between the standard deviation of the estimates implied by the model and the actual income differences across states over time. Figure 3 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, which is underpredicted in the model.

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 30 years, it would be less than a tenth of its starting value. 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. In other words, convergence would be faster if all states realized the same values for the explanatory variables. We now consider each of these factors in turn.

Knowledge Variables

All of the coefficients of the knowledge variables (high school+, college+, and patent stocks) have the expected sign and are statistically significant. Each plays a role in enabling some states to achieve and maintain higher per capita personal income relative to other states. 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 small. In 1999 (the lag used for 2004), high school attainment for these states averaged 83.3 percent. Even so, there remains a fairly wide range of achievement rates. West Virginia has the lowest rate of high school attainment at 75.1 percent, while Washington's stands at 91.2 percent.

Similarly, we find a positive and statistically significant effect for the log of the deviation from the states' average in the percent of the population that are college graduates. 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).

Our patent-stock variable measures a different dimension of knowledge, a state's ability to innovate new products and production techniques. 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 4 compares the implied effects of the knowledge 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 figure also includes 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. Clearly, some of the effects are offsetting as the standard deviation of all variables is not much higher than just the patent effect alone. Finally, note that because of the decline in the variation across states of high school attainment the role of this factor declines noticeably over time, while differences in college attainment are more persistent, and end up being more important than the high school effect.

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 5 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.

Other Variables

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 Schumpeterian creative destruction, 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. This is broadly consistent with the literature, which reports little effect of state banking activity on states' per capita income growth (see McPherson and Waller, 2000).

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 6 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

In this section, we describe how our results vary as we estimate the model under different distributional assumptions, allow the model's parameters to differ over time, change the lag lengths used in the estimation, and alter the depreciation rates used in constructing the stock variables. Under all these perturbations, our central finding remains the same: The knowledge variables, particularly patents, are the key to understanding how some states persistently outperform others in terms of per capita income.

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. Note that the climate variables, being constant over time, are stripped out of the model, as are any unobserved time-constant variables that this technique is designed to handle. The estimates do differ some from the baseline estimates, and 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). In fact, 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.

The climate variables appear to have more explanatory power than the state dummies. If the dummy variables for four states are excluded from the model, the climate variables can be reintroduced to the model. By selecting four states with similar

[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.

climate variables and small estimated state dummies (Mississippi, Alabama, Louisiana, and South Carolina), the remaining state dummies are centered about zero. An F-test for the statistical significance of the remaining state dummies cannot be rejected at the 95 percent confidence level. In any case, if you believe the fixed effects estimator should be the preferred one, our core findings remain unchanged.

Figure 7 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 6 (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 is to allow 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 over time, either due to changes in technology or changes in 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, if anything, 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. An F-test for whether these coefficients are all equal cannot be rejected at the 95 percent confidence level (p-value 0.0556).

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 to estimate them with.

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 8. The main observable shift from Figure 6 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 6) 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 9).

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 even more robust across this dimension. 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), and the same knowledge variables explain the bulk of the variation in per capita personal incomes across states (see Figure 10). The time paths are more volatile in this figure because the patents and highway variables are not inherently smoothed as they are when they are treated as stocks, but they tell essentially the same story.

V. A Closer Look at States

More insight into how per capita personal income evolves can be gained by looking at individual states. A couple basic facts are illustrated in Figures 11 and 12, which plot the observed relative per capita incomes across states for 1939 and 2004, respectively. First, these plots show in more detail than Figure 1 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. In other words, there is a role for factors other than convergence to explain this variation.

Figures 13 and 14 plot the predicted effects of our explanatory variables for 1939 and 2004, respectively. In both periods, high-performing states have large patent stock and educational attainment effects, while for low-performing ones these effects are large and negative. Industry structure and all the other explanatory effects play relatively minor roles. In particular, education plays a much larger role in 1939, when high school attainment varied much more across states. For example, Mississippi trailed all other states in both periods in per capita personal income, but while it has not managed to reduce the drag from its relatively low stock of patents, by 2004 it had substantially narrowed the gap in educational attainment between it and the average state. Connecticut, on the other hand, is a high-income state in both periods. In 1939, its higher levels of personal income were driven by a relatively high stock of patents, but in 2004 its relatively high level of educational attainment also played a significant role.

While effects predicted for a given period are of interest, they do not reflect the full impact of the explanatory variables over time, 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 15 and 16. There are differences in the estimates for individual states, but the overall cumulative effects are very similar for the two techniques. The estimated effects are particularly close for the patent-stock and educational-attainment effects. Most of the differences come from industry-structure and other effects. This is not too surprising because although the coefficients on manufacturing and mining are statistically significant in the baseline model, none of the industry-structure coefficients are statistically significant in the fixed effects model (see Table 3). Consequently, their estimated effects are likely to contain a lot of noise. Also, because the effects of the climate variables are included in the "other" category in the baseline results but not in the fixed effects results (time-invariant climate variables are removed by the fixed effects estimator) the baseline and fixed effects estimates of the other effects are likely to differ.

Looking at only Figures 13 and 14, one might get the impression that while states may be able to influence their relative position, their ability is somewhat limited. After all, the best and worst states only affect their relative per capita personal incomes by less than 10 percent. However, one gets a very different impression by looking at the estimated cumulative effects. 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. After 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 find that a state's productive stock of knowledge appears to enhance its relative level of per capita income.

To examine the differences in relative levels of per capita income among the 48 contiguous states from 1939 to 2004, 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 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.

Our results are easily summarized: A state's stock of knowledge is the main factor explaining its relative level of per capita personal income. 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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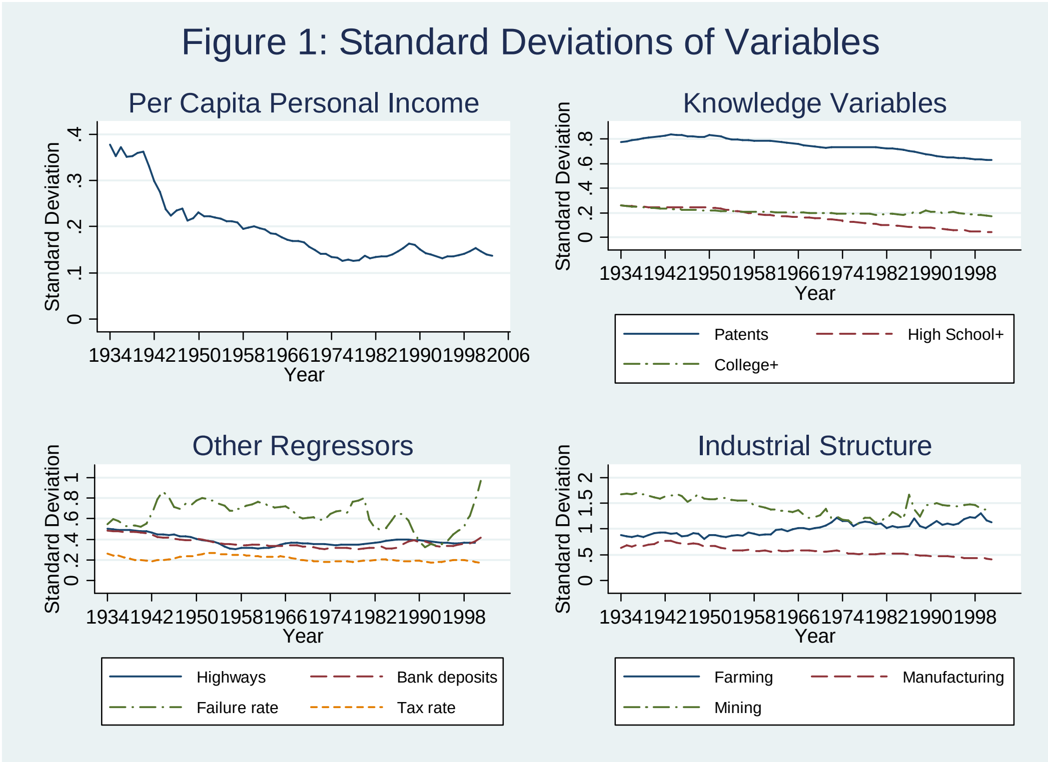


Figure 1: Standard Deviations of Variables
Per Capita Personal Income
Standard Deviation
Year
Knowledge Variables
Patents
High School+
College+
Other Regressors
Highways
Bank deposits
Failure rate
Tax rate
Industrial Structure
Farming
Manufacturing
Mining

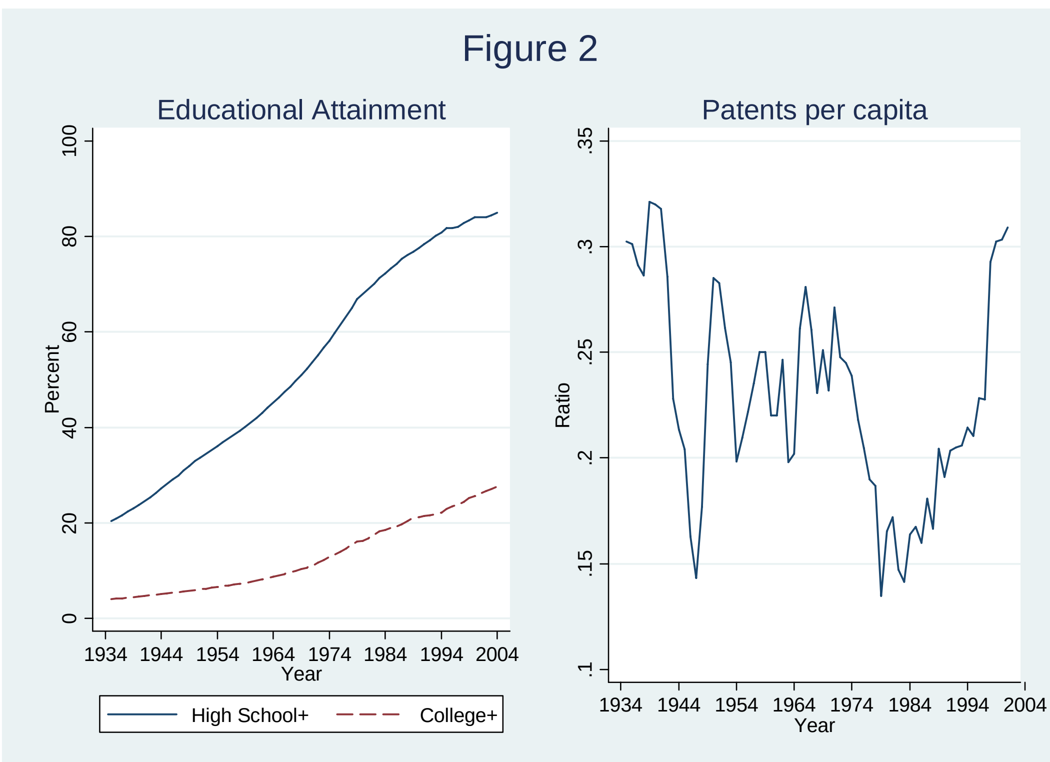


Figure 2
Educational Attainment
Percent
Year
High School+
College+
Patents per capita
Ratio

Figure 3: Model Implications for Income Convergence

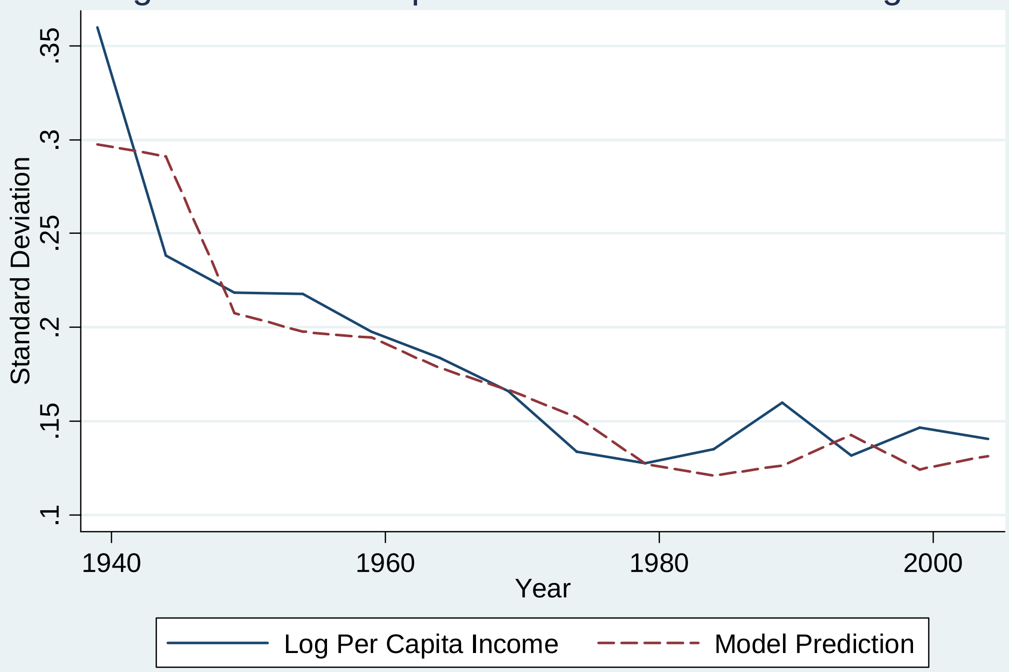
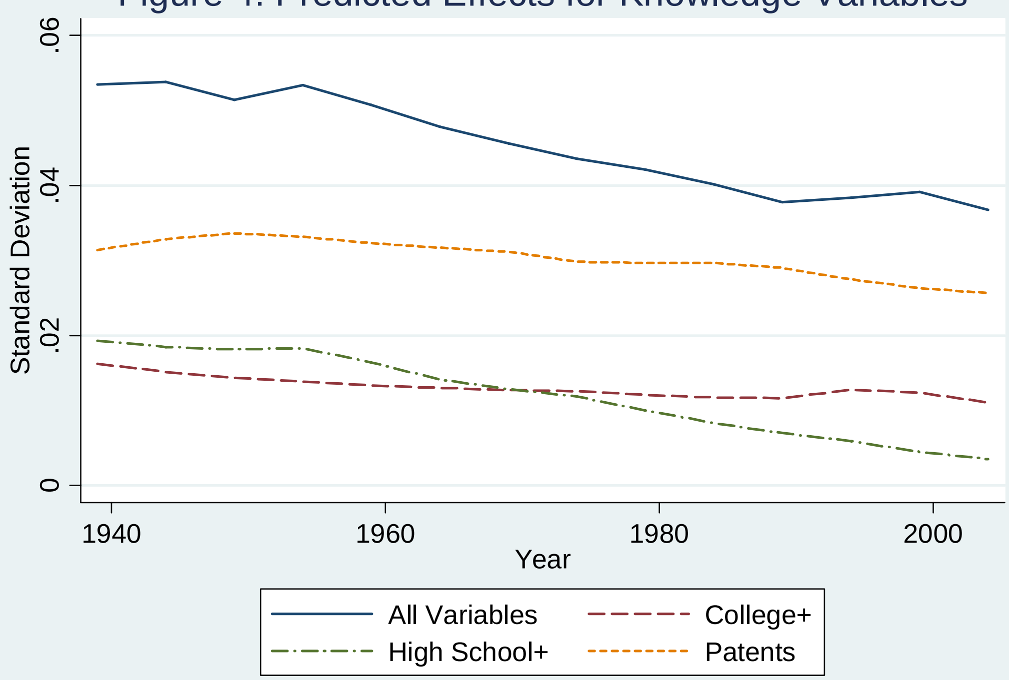


Figure 4: Predicted Effects for Knowledge Variables



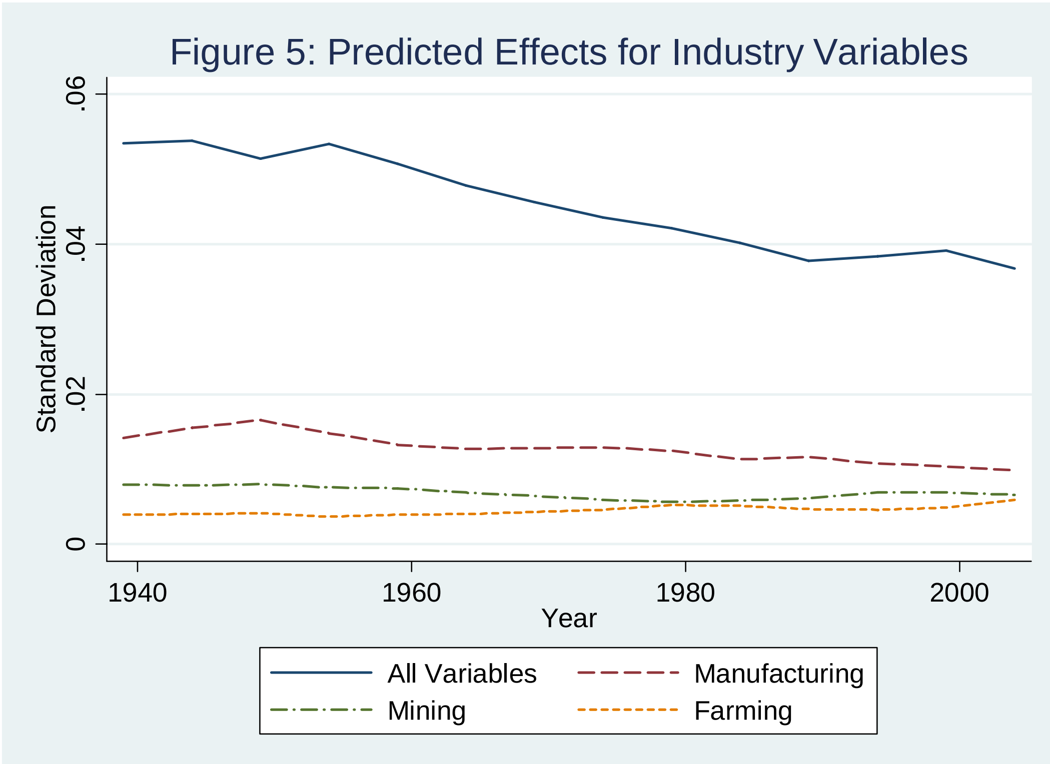


Figure 5: Predicted Effects for Industry Variables
Standard Deviation
0
.02
.04
.06
1940
1960
1980
2000
Year
All Variables
Manufacturing
Mining
Farming

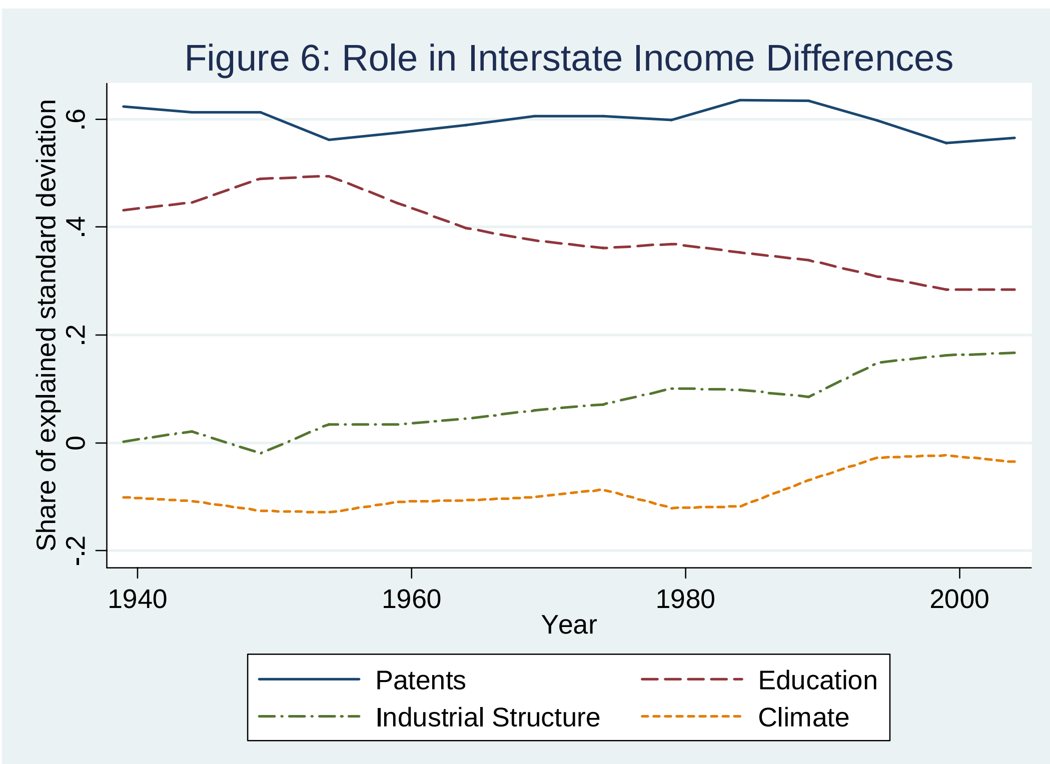


Figure 6: Role in Interstate Income Differences
Share of explained standard deviation
-.2
0
.2
.4
.6
1940
1960
1980
2000
Year
Patents
Education
Industrial Structure
Climate

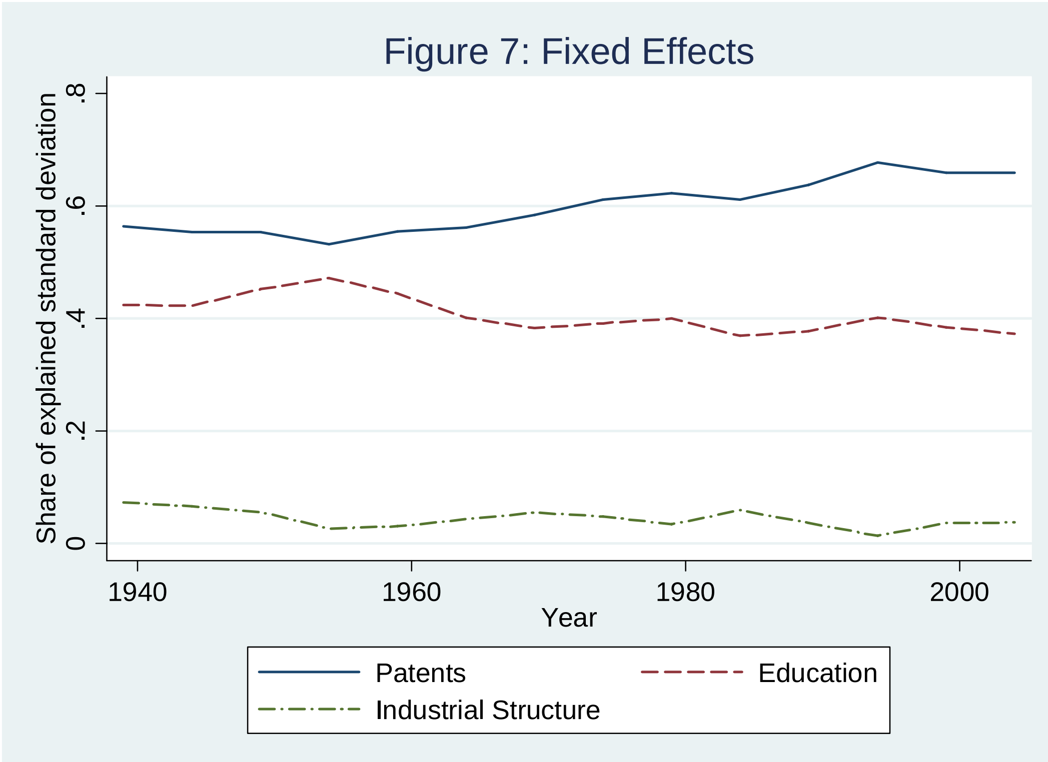


Figure 7: Fixed Effects
Share of explained standard deviation
0
.2
.4
.6
.8
1940
1960
1980
2000
Year
Patents
Education
Industrial Structure

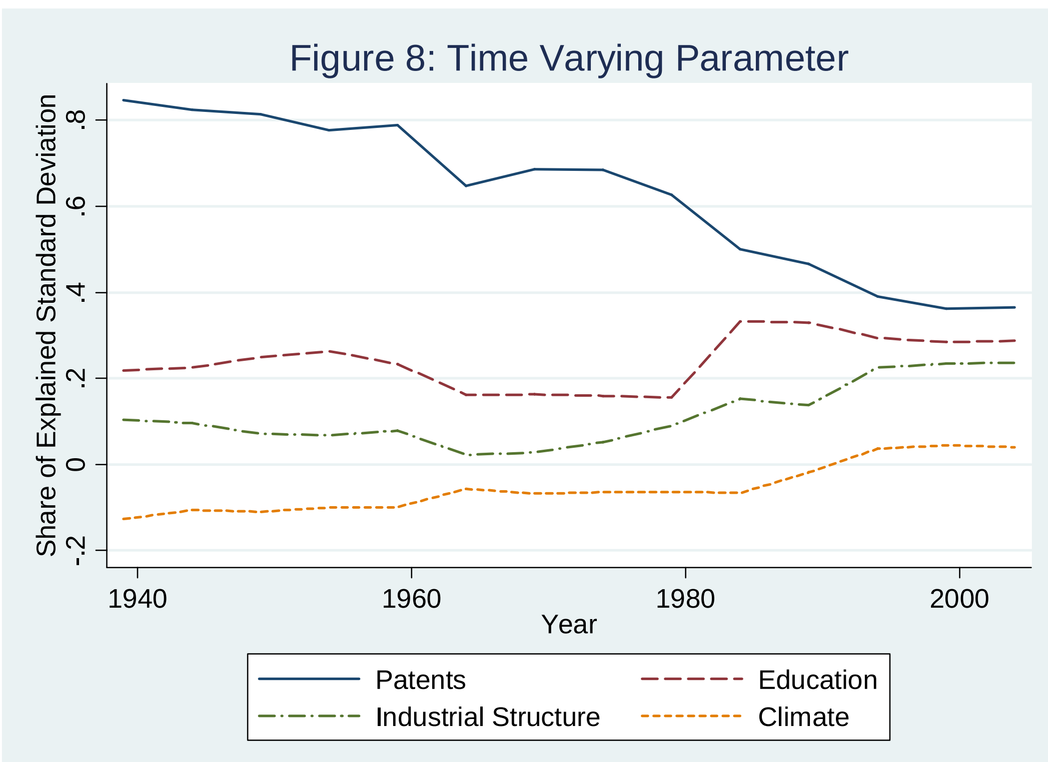


Figure 8: Time Varying Parameter
Share of Explained Standard Deviation
-.2
0
.2
.4
.6
.8
1940
1960
1980
2000
Year
Patents
Education
Industrial Structure
Climate

Figure 9: Baseline Model Lag=10

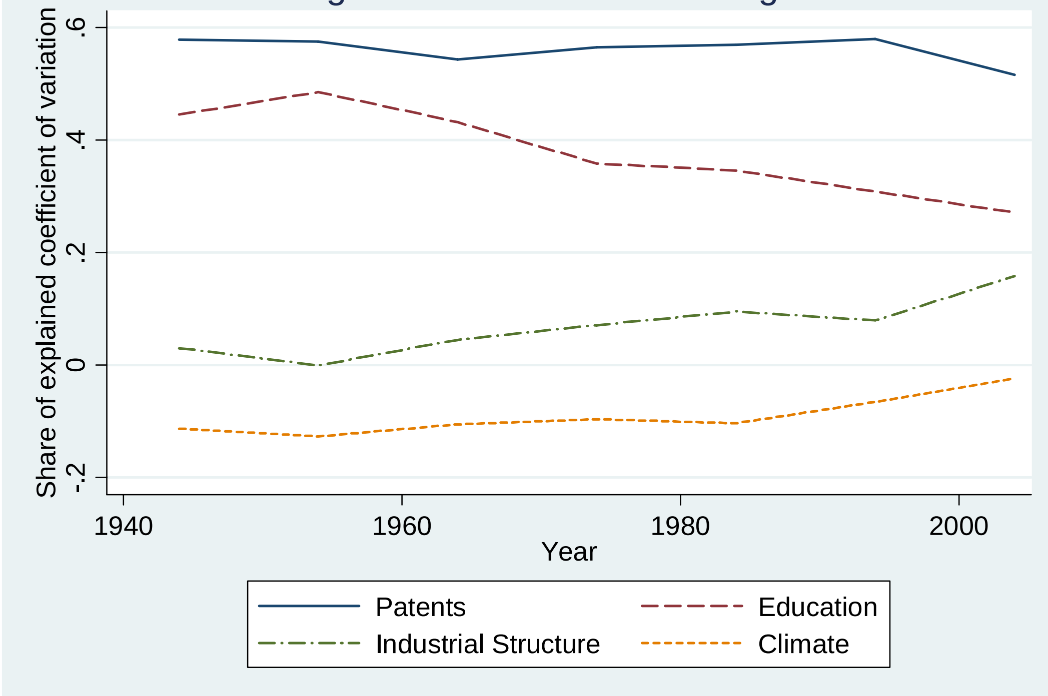


Figure 10: Baseline Model Depreciation=100%

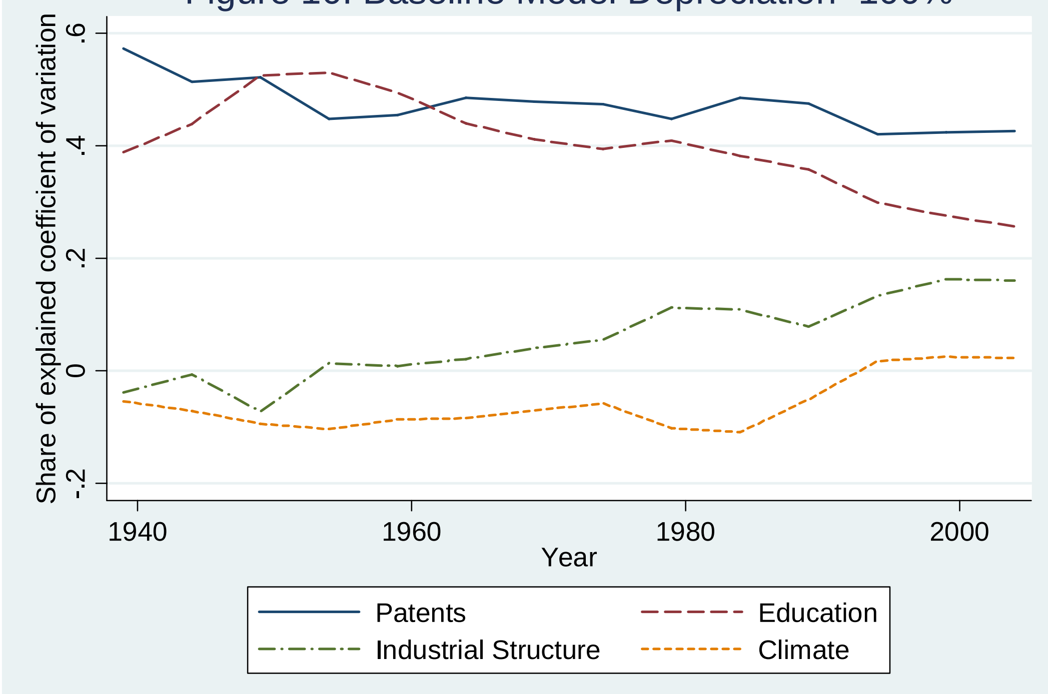


Figure 11

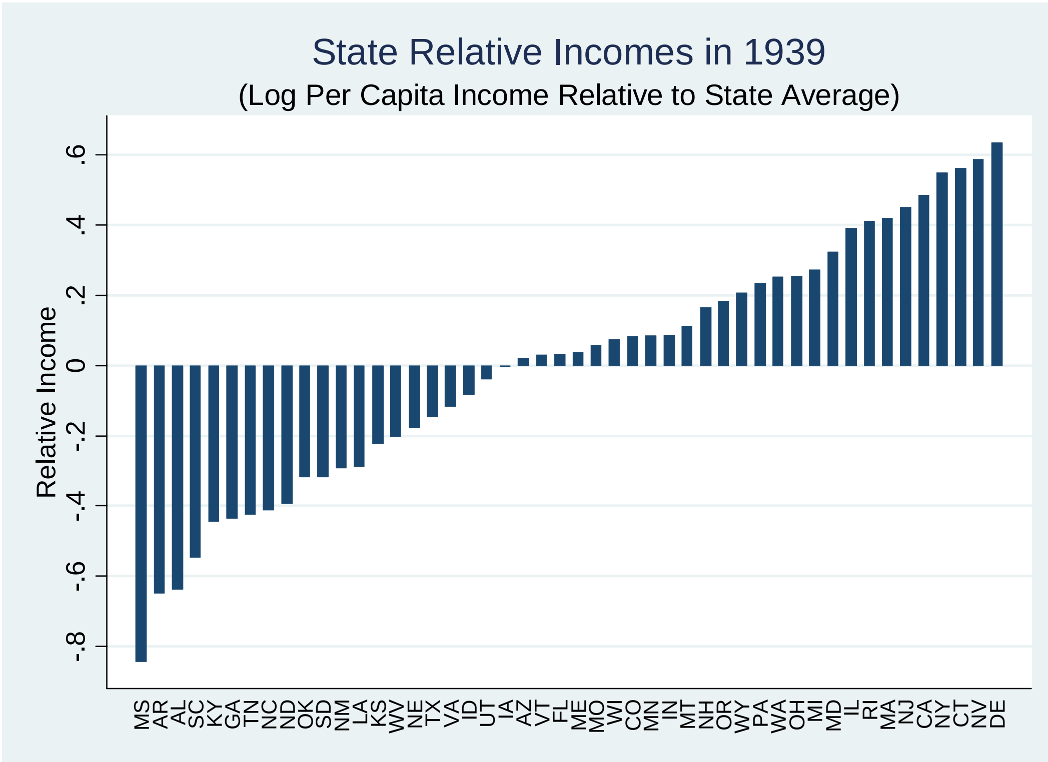


Figure 12

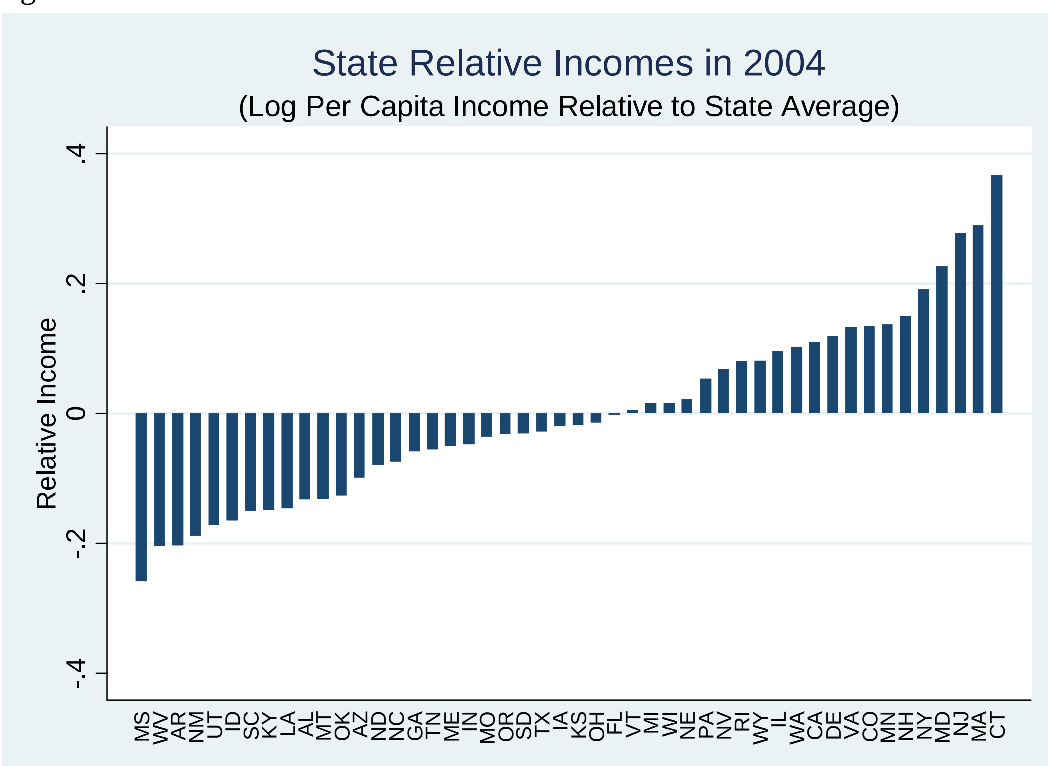


Figure 13: Baseline

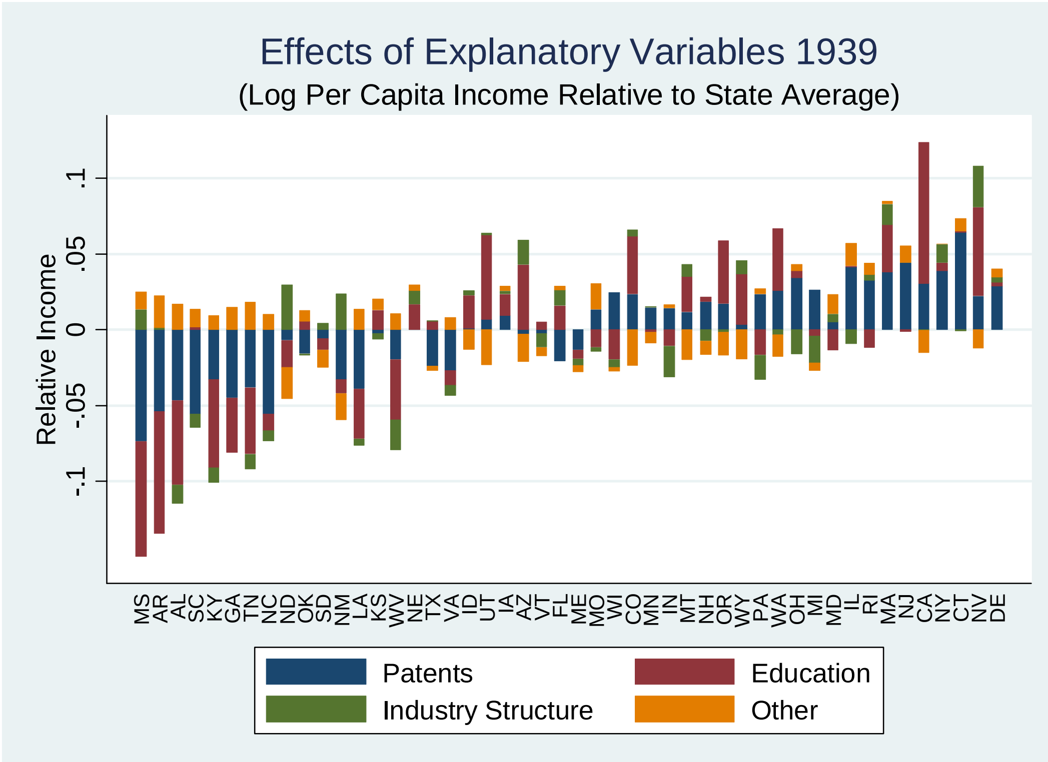


Figure 14

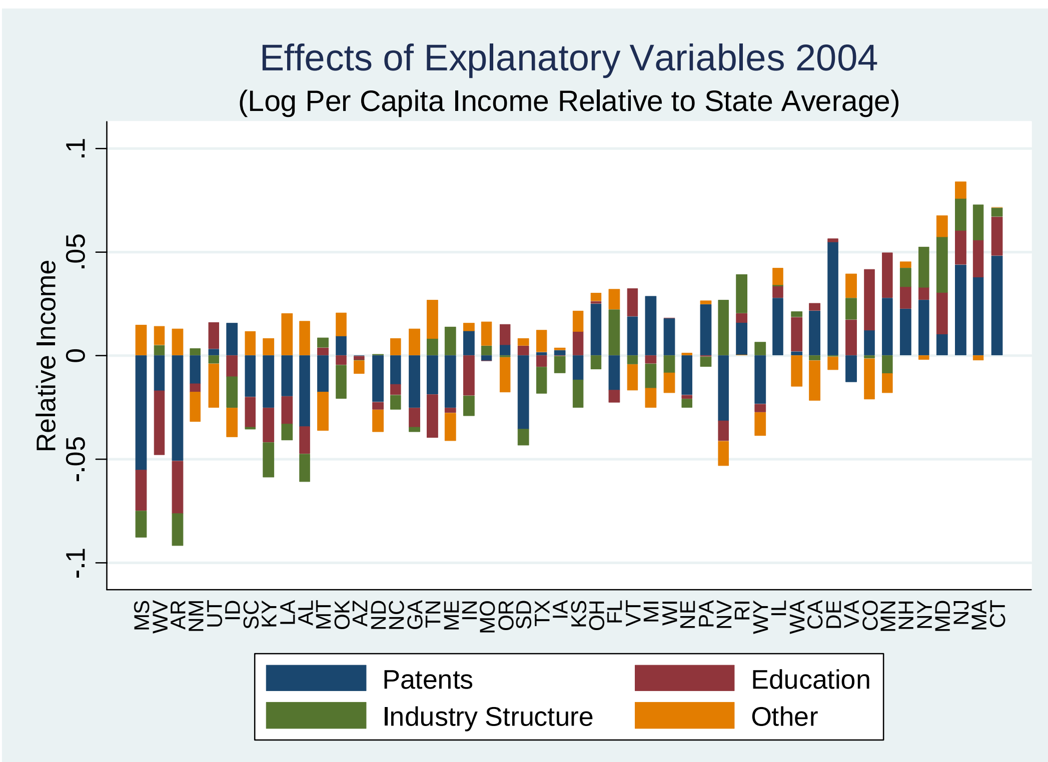


Figure 15: Baseline

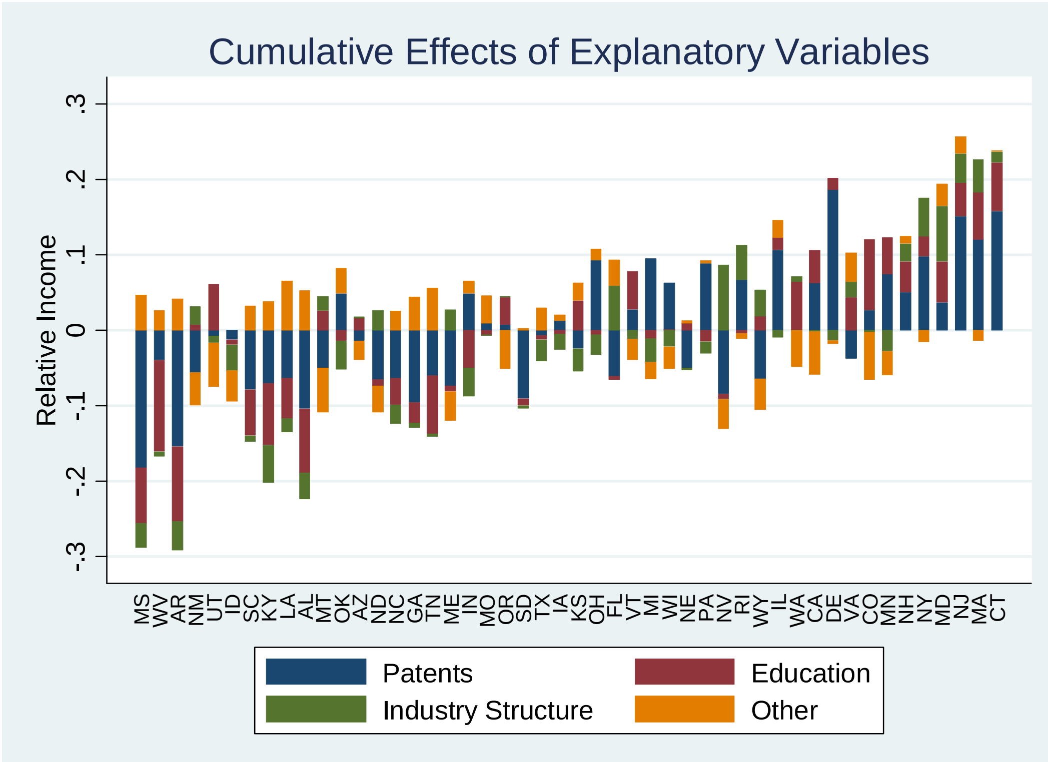


Figure 16: Fixed Effect

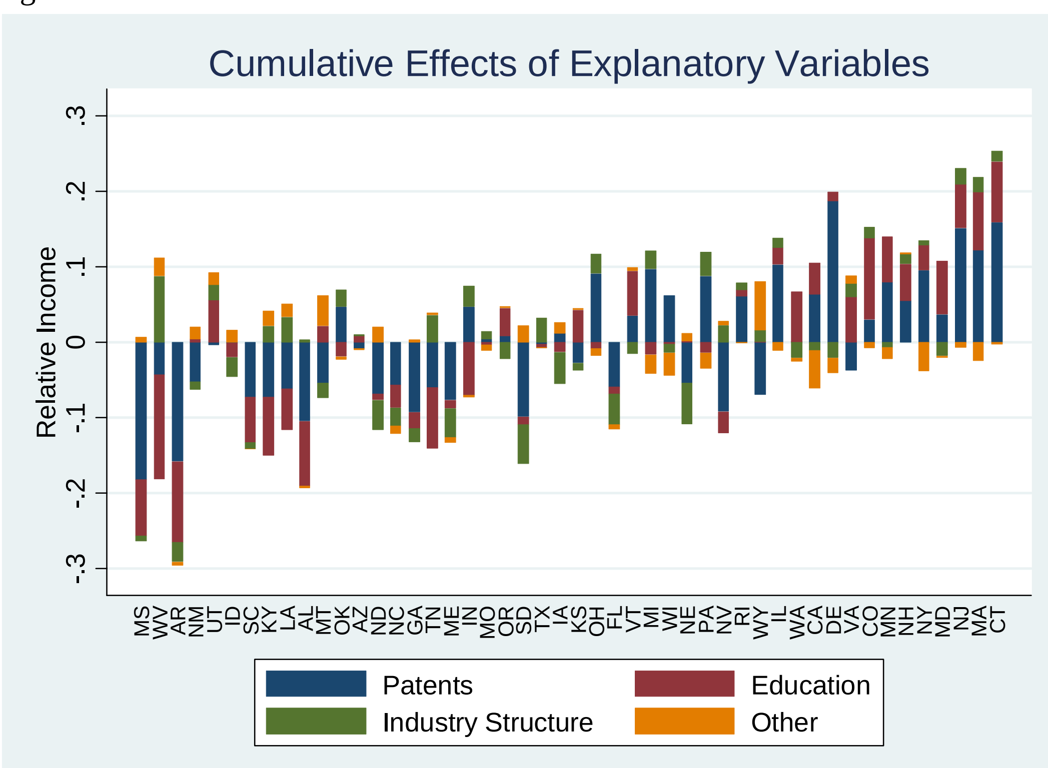


Table 1: Values of Selected Variables

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%