# Many Types of Human Capital and Many Roles in U.S. Growth: Evidence from County-Level Educational Attainment Data*

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*Abstract*

We utilize county-level data to explore the roles of different types of human capital accumulation in U.S. growth determination. The data includes over 3,000 cross-sectional observations and 39 demographic control variables. The large number of observations provides enough degrees of freedom to obtain estimates for the U.S. as a whole and for 32 states in and of themselves. This data contains measures of educational attainment for four distinct categories: (a) 9 to11 years, (b) high school diploma, (c) some college and (d) bachelor degree or more. These variables represent human capital stocks for each and every county. This is a departure from much of the economic growth literature which has (at least in part) relied on extrapolation of stocks from flows, e.g. school enrollment data. We use a consistent two stage least squares estimation procedure. We find that (i) the percentage of a county's population with less than a high-school education is negatively correlated with economic growth, (ii) the percentage obtaining a high school diploma is positively correlated with growth, and (iii) the percentage obtaining some college education has no clear relationship with economic growth but (iv) the percentage that obtains a bachelor degree or more is positively correlated with growth. Further, we find that (v) there is significant qualitative heterogeneity in estimated coefficients across states for the 9 to 11 years and high school diploma categories but (vi) no qualitative heterogeneity for the college level categories. The most consistent conclusion across samples is that the percent of a county's population obtaining a bachelor degree or higher level of college education has a positive relationship with economic growth. Oddly enough, despite findings (ii), (iv) and (vi) above, we find that the percentage of a county's population employed in educational services is negatively correlated with economic growth.

## 1. Introduction

Does human capital accumulation contribute to the economic growth and in what way(s)? This has been a fundamental query for policy-makers, educators and scholars.

One perspective from which to view this query is a macroeconomic one, and the view from this perspective is not straightforward. Human capital accumulation may allow a populace to better obtain and use the technologies already existing world-wide (raising an economy's balanced growth *path*), or instead it may allow a populace to better produce new, previously-nonexistent technologies (raising an economy's balanced growth *rate*). The perspective is further clouded by data limitations. For many economies, human capital *stock* data is unavailable and must be extrapolated (imperfectly) from human capital flows, creating measurement error. Furthermore, there are many types of human capital with potentially many different contributions to economic growth. Macroeconomic data often aggregates away this heterogeneity.

This paper analyses the role of human capital accumulation in U.S. income growth determination. County-level data allows us to explore different roles of different types of human capital accumulation. The data includes over 3,000 cross-sectional observations and 39 demographic control variables. The large number of observations provides enough degrees of freedom to provide estimates for the U.S. as a whole and for 32 states in and of themselves. Our human capital measures are of educational attainment and cover four distinct categories: percent of a population with (a) 9 to11 years of school and no more, (b) with a high school diploma and no more, (c) with some college, and (d) with a bachelor degree or more. We find significant heterogeneity in estimated effects across the four types of human capital, as well as across individual U.S. states. Only one estimated effect of human capital in growth determination is (i) clearly detected in the full U.S. sample and (ii) consistent in that no state-wide sub-sample provides statistically significant evidence to the contrary: *the percent of a county's population having attained a bachelor degree or higher level of education is positive associated with economic growth.*

The variables we use as a measure of human capital offer two important advantages. First, they represent human capital stocks for each and every county. This is a departure from much of the economic growth literature which has (at least in part) relied on extrapolation of stocks from flows. For example, Mankiw et al (1992) use school-enrollment rates as a human capital investment proxy for human capital stocks in cross-county growth regressions.[1,2] As well, Kyriacou (1991) and Barro and Lee (1993) combine limited educational attainment observations with school-enrollment data to estimate human capital stocks for international samples. Second, our four-level categorization provides a distinction between different levels/types of human capital accumulation. Mankiw et al (1992) use data on high-school enrollment in their regressions. Klenow and Rodriguez-Claire (1997) add elementary and college enrollment variables to their analysis. Our data adds a distinction between more or less college-level education that we find to be economically important in our results.[3] It should also be noted that none of the above studies use county-level data.

Besides the fine categorizations of human capital levels/types and the exceptionally large number of cross-sectional observations, the data offers numerous other advantages over the international data often used in identifying growth determination processes. A single institution collects the data, ensuring considerable uniformity of variable definitions. There is no exchange rate variation between the counties and the price variation across counties is smaller than across countries. Also, U.S. counties are characterized by exceptional mobility of technology, resources and factors of production. Of course, many of these advantages are embodied in U.S. state-level data used by, e.g., Barro and Sala-i-Martin (1991) and Evans (1997a). However, the state level data sacrifices the large number of observations that the county-level data offers. This large number of observations, and accompanying degrees of freedom, allows

[1] Mankiw et al (1992), working from the neoclassical growth model, actually derive a regression specification in terms of physical and human capital flows instead of stocks. However, doing so requires an assumption that countries in their sample are currently on their balanced growth paths.

[2] We also have variables representing school enrollment at public elementary level, private elementary level, public nursery level, and private nursery level. These variables are included in the full U.S. sample regressions. However, the related coefficient values were estimated to be 0 to four decimal places. Therefore, to preserve degrees of freedom, they were not included in the within-state regressions.

[3] Barro and Lee (1993) develop a 7-level categorization, adding finer distinction within the elementary and high-school level years of attainment. However, their measures are extrapolated from flows for over 50 percent of their observations and are for a sample of 129 countries. Our measures are stocks and focus entirely on one country: the U.S. Further, Barro and Lee do not pursue growth regressions in their own study.

for a more detailed analysis of the roles of human capital in the U.S. by addressing inter-state heterogeneity for 32 states.[4]

The primary contribution of this paper to the empirics of human capital and growth lies in the extensive dataset that we have constructed. However, we also utilize a consistent two stage least squares (2SLS) estimation procedure of a specification derived from the neoclassical growth model, as suggested by Evans (1997a, 1997b). Evans (1997b) demonstrates that data must satisfy highly implausible conditions for ordinary least squares (OLS) estimators to be consistent. (OLS is used by most studies with a neoclassical specification, e.g. Barro and Sala-i-Martin (1991, 1992) and Mankiw et al (1992).) Evans proposes a 2SLS method that produces consistent estimators.[5]

The neoclassical specification employed in this paper plays a role in interpreting human capital's role(s) in growth determination. As mentioned above, human capital can be hypothesized to have a role in technology *adoption* (balanced growth path effect) and/or technology *development* (balanced growth rate effect). These effects are, of course, not mutually exclusive, but understanding which, if either, is predominant seems to be important. Benhabib and Spiegel (1994) explore this question for a cross-country sample and find that the adoption effect is more important. Our neoclassical specification allows us to consider the same question for the U.S. in and of itself. As detailed in Section 2 below, with the average growth of income as the dependent variable, the estimated value of the coefficient on the initial income level provides a discriminating test. A negative value suggests that the neoclassical growth model (i.e. human capital aids adoption) is the better approximation to reality than an endogenous growth model (i.e. human capital aids development). As outlined below, and documented fully in Young et al (2003), this coefficient is negative and significant for the full U.S. sample and negative for every individual state sample where the value was statistically significant. This allows us to not only ascertain the correlation of human capital types with economic growth, but also to offer an interpretation supported by the data. The

[4] A full 29 of our states have counties numbering more than 50 (the number of U.S. states) each.
[5] We have previously employed this 2SLS estimation with the county-level data to study convergence within the U.S. (Higgins et al, 2003) and heterogeneity in convergence rates across U.S. states (Young et al, 2003).

criterion we use for reporting 32 states is that their regressions yielded significant initial income coefficient estimates, thus supporting the neoclassical specification.

Using county-level data on human capital stocks and the consistent 2SLS estimation, we find that (i) the percentage of a county's population with less than a high-school education is negatively correlated with economic growth, (ii) the percentage obtaining a high school diploma is positively correlated with growth, (iii) the percentage obtaining some college education has no clear relationship with economic growth but (iv) the percentage that obtains a bachelor degree or more is positively correlated with growth. Further, (v) there is significant qualitative heterogeneity in estimated coefficients across states for the 9 to 11 years and high school diploma categories but (vi) no qualitative heterogeneity for the college level categories. A broad conclusion is that *individual* high levels of human capital accumulation are conducive to the adoption and application of available technologies, and that this represents a positive contribution to economic growth via a higher balanced growth path.

An additional, and surprising, finding which we briefly discuss in this paper concerns another demographic variable included in our regressions: percentage of a county's population employed in the education services industry. Based on the above findings we would expect the coefficient on this variable to be positive or not significantly different from zero. In fact, we report that it is negative and significant for the full sample *and* for every individual state sample where the estimate is significant at the 10 percent level or better!

The paper is organized as follows. Section 2 discusses the econometric specification of the neoclassical growth regression and the 2SLS technique we employ. Section 3 describes the county-level data. Section 4 briefly describes the convergence rate parameter estimates on which our interpretation of human capital coefficient estimates rests. The estimates of contributions from different types/levels of human capital for full and individual U.S. state samples are presented and discussed in section 5. Section 6 briefly touches upon the finding that the prevalence of educational service employment is negatively correlated with economic growth. Section 7 concludes.

## 2. Econometric Model and 2SLS Estimation Procedure

The basic specification used here and in other cross-sectional growth regressions arises from the neoclassical growth model of Ramsey (1928), Solow (1956), Swan (1956), Cass (1965) and Koopmans (1965).[6] The growth model implies that,

$$\hat{y}(t) = \hat{y}(0)e^{-Bt} + \hat{y}^{*}(1 - e^{-Bt}) \tag{2.1}$$

where $\hat{y}$ is log of income per effective unit of labor (technology assumed to be labor augmenting), $t$ is the time period (0 being the initial time period), and $B$ is a nonlinear function of the economy's discount (average, subjective), population growth, and technological growth rates, as well as preference parameters. $B$ governs the speed of adjustment to the steady state. The $\hat{y}^{*}$ is the economy's steady-state log level of income per effective unit of labor. From (2.1) it follows that the average growth rate of income per unit of labor between dates 0 and $T$ is,

$$\frac{1}{T}\left(y(T) - y(0)\right) = z + \left(\frac{1 - e^{-BT}}{T}\right)\left(\hat{y}^{*} - \hat{y}(0)\right) \tag{2.2}$$

where $z$ is the exogenous rate of technical progress and $B$ represents the responsiveness of the average growth rate to the gap between the steady state of log income per effective unit of labor and the initial value. Since effective units of labor ($L$) are assumed to equal $Le^{zt}$, we have $\hat{y}(0) = y(0)$.

From this model, growth regressions are obtained by using OLS to fit cross-sectional data on economies 1,…, $N$ to the equation,

$$g_n = \alpha + \beta y_{n0} + \gamma' x_n + v_n . \tag{2.3}$$

In (2.3), $g_n$ is the average growth rate of per capita income for economy $n$ between years 0 and $T$ [i.e., $\frac{1}{T}\left(y(T) - y(0)\right)$], $\alpha$ is a constant that is a function of z, $\beta = \left(\frac{1 - e^{-BT}}{T}\right)$, $x_n$

[6] A derivation of the baseline specification from the growth model is provided by Barro and Sala-i-Martin (1992).

is a vector of variables that control for cross-economy heterogeneity in determinants of the steady-state, $\hat{y}^*$, $\gamma$ is a vector of coefficients on those variables, and $\nu_n$ is the error term assumed to have zero mean and finite variance.

An estimate of $\beta$ provides a discriminating test between the neoclassical growth model, where technological change is exogenous and, therefore, human capital affects growth through better adoption of existing technologies, and endogenous growth theories where human capital accumulation may affect technological change directly. If $\beta < 0$, then $\gamma$ describes how the $x_n$ affect the height of economy $n$'s balanced growth *path*. Otherwise, $\gamma$ describes how the $x_n$ affect $n$'s balanced growth *rate* (Evans, 1997b, pp.3-4).

However, Evans (1997b) shows that OLS estimates of $\beta$ and $\gamma$ will be consistent only when the data satisfy highly implausible conditions. Plausible departures from these conditions can produce large biases. Specifically, Evans demonstrates that unless (i) the dynamical structures of the economies examined have identical, first-order autoregressive representations, (ii) every economy affects every other economy symmetrically, and (iii) the set of conditioning variables controls for all permanent cross-economy differences, the OLS estimators of the speed of convergence are inconsistent. They are biased downwards, underestimating the speed of convergence.

Evans (1997b) proposes a 2SLS instrumental variables approach that consistently estimates the speed of convergence as well as the effects of conditioning variables. We use a cross-section variant of his method. The method consists of two stages. In the first stage we use instrumental variables to estimate the equation,

(2.4) $$\Delta g_n = \omega + \beta \Delta y_{n0} + \eta_n ,$$

where

$$\Delta g_n = \frac{(y_{n,T} - y_{n,0})}{T} - \frac{(y_{n,T-1} - y_{n,-1})}{T} ,$$

$\Delta y_{n0} = y_{n0} - y_{n,-1}$, $y_n$ is the logarithm of per capita income for county $n$, $\omega$ and $\beta$ are parameters, and $\eta_n$ is the error term. We use the lagged (1969) values of all the independent variables as instruments, with the exception of Metro Area, Water Area, and Land Area.[7] Given the sample period we use here, we define,

$$\Delta g_n = \frac{(y_{n,1998} - y_{n,1970})}{T} - \frac{(y_{n,1997} - y_{n,1969})}{T}.$$

Next, define $\beta^*$ as the estimator obtained from equation (2.4). In the second stage, we take the estimate for $\beta^*$, multiply it by $y_{n0}$ and then subtract the product from $g_n$. This yields a variable,

(2.5) $$\pi_n = g_n - \beta^* y_{n0},$$

which is then regressed (using OLS) on an intercept and the vector of variables, $x_n$, that are potential influences on balanced growth path levels. This second-stage regression is of the form,

(2.6) $$\pi_n = \tau + \gamma x_n + \varepsilon_n,$$

where $\tau$ and $\gamma$ are parameters and $\varepsilon_n$ is an error term. This regression yields a consistent estimator, $\gamma^*$. Also note that $\tau$ is the same, in principle, as the OLS $\alpha$. It is an estimate of the exogenous rate of technical progress, *z*, or the balanced growth *rate*.

What this two stage procedure essentially does is, in the first stage, differences out any uncontrolled form of heterogeneity from the specification so that an omitted variable bias does not occur[8] and then, in the second stage, uses the resulting estimate of

[7] See the data appendix for details.
[8] The derivation of this equation (see Evans (1997b)) depends on the assumption that the conditioning variables are (approximately) constant during the time frame considered, allowing them to be differenced out. We are indebted to Nazrul Islam for pointing out that, while this is a reasonable assumption for many conditioning variables in the literature (e.g., an index of democracy for an international sample over 15 years), many of our county-level conditioning variables potentially vary significantly (e.g., the percent of the population employed in the communications industry over 28 years). To make sure that this did not introduce significant omitted variable bias into our estimations we ran the three first stage regressions for the full U.S. sample with differenced values of all conditioning variables included as regressors. All point estimates of $\beta$ from the modified first stages fell within the 95 percent confidence intervals of the Evans method first stage estimates. As well, if the $\beta$ estimates are not significantly affected then neither are the second stage results (see below).

 to recreate the component of a standard growth regression that would be related to the set of conditioning variables. This component can then be regressed on a constant and the conditioning variables, in "un-differenced" form, to estimate the effects of conditioning variables on balanced growth paths. This procedure ensures that none of the information contained in the levels of the conditioning variables is lost.[9]

Besides reporting OLS results below, as well as 2SLS results, for comparison, we also use a Hausman test as an additional aid in the determination of the appropriateness of the instrumental variable approach for the full U.S. sample. Two separate tests were performed. The first test was run on the $\beta$ values and yielded an $m$ value of 134.6. The second test was run on the entire model and yielded an $m$ value of 1236.6. Indeed, both tests reject the null hypothesis at the 1% level, thereby suggesting that the OLS estimates are inconsistent.

## 3. U.S. County-Level Data

The data for this study were drawn from several different sources. The majority of the data, however, came from the Bureau of Economic Analysis Regional Economic Information System (BEA-REIS) and U.S. Census data sets.[10] The BEA-REIS data are largely based on the 1970, 1980 and 1990 decennial Census summary tape files, the 1972, 1977, 1982 and 1987 Census of Governments, the Census Bureau's City and County Book from various years. All dollar variables are expressed in constant 1992 prices. Natural logs were used throughout the project. We exclude military personnel from the measurements of both personal income and population.

Our entire data set includes 3,058 county-level observations.[11] We examine the full sample, as well as U.S. states as economic units in and of themselves. We report

[9] This is a point on which Barro (1997, p.37) has criticized panel data methods. As they rely on time series information, the conditioning variables are differenced. However, the conditioning variables often vary slowly over time such that the most important information is in the levels.

[10] We thank Jordan Rappaport for kindly sharing with us some of the data used in this study.

[11] The original data set contained 3,066 observations. Eight counties, however, were excluded from the data set for various reasons. Primarily, counties were excluded for lack of data. Examples of counties that fell into this category include counties in northern Alaska and some counties in Hawaii. Some data for these counties were simply not recorded as far back as 1970. Furthermore, in Virginia, some cities are themselves independent counties. If the data for these independent cities were available we let them stand as their own county. However, if the data were not available, then we tried to incorporate the independent city into the surrounding county. If that was not feasible, it was then dropped from the data set.

estimation results for 32 of the 50 states. The standard we used for inclusion was whether or not, in the first-stage regressions, the estimate for $\beta$ was statistically different from zero.

The measure we use for personal income is that of the U.S. Bureau of Economic Analysis (BEA).[12] The definitions that are used for the components of personal income for the county estimates are essentially the same as those used for U.S. national estimates. For example, the BEA defines "personal income" as the sum of wage and salary disbursements, other labor income, proprietors' income (with inventory valuation and capital consumption adjustments), rental income (with capital consumption adjustment), personal dividend income and personal interest income. (BEA, 1994) "Wage and salary disbursements" are measurements of pre-tax income paid to employees. "Other labor income" consists of payments by employers to employee benefit plans. "Proprietors' income" is divided into two separate components—farm and non-farm. Per capita income for a county is defined as the ratio of this personal income measure for the county to the population of the county. We adjust the personal income measure to be net of government transfers and express the value in per capita 1992 dollars using the U.S. GDP deflator. Natural logs of the real per capita income measures are used in the analysis.[13]

In addition to the per capita income variable we also utilize 39 demographic conditioning variables. In **Table 1** we provide the complete list of the variables we use in this study along with their definitions. In the table we also provide the source of each series as well as the period it covers. All 39 of these variables were used for estimation using the full sample. However, only 33 of these were used for the with-in state estimations to preserve degrees of freedom. Our standard for exclusion was that a conditioning variable, in the second-stage regression using the full sample, resulted in a coefficient estimate with zeros to at least the fourth decimal place (0.0000). The variables excluded from the within-state regressions were "land area," "water area," "education: public elementary," "education: public nursery," "education: private elementary," and "education: private nursery."

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[12] The data and their measurement methods are described in detail in "Local Area Personal Income, 1969–1992" published by the BEA under the Regional Accounts Data, February 2, 2001.
[13] See the Data Appendix at the end of this paper for more detailed descriptions of the personal income measure.

The variables that we focus on in this paper are four educational attainment variables: "Education: 9-11 years," "Education: H.S. diploma," "Education: Some college," and "Education: Bachelor +."[14] Each variable represents the percentage of a county's population that has obtained its named level of education and no higher. The delineations and cut-offs for educational attainment are intuitive and also those used by the U.S. census. Initial values for each of the four variables were collected from the 1970 U.S. Census tapes. The data is based on self-reported values from the census surveys.

## 4. Motivating a Neoclassical Interpretation of Human Capital

The OLS and 2SLS estimates of $\beta$, the coefficient on the log of 1970 per capita income, are presented in **Table 2** for the full U.S. sample and for 32 individual U.S. states. The speed of conditional convergence can be inferred from $\beta$. Associated with these estimates of $\beta$, **Table 3** reports the asymptotic (conditional) convergence rates and corresponding 95 percent confidence intervals.[15]

For the full sample, the significant and negative $\beta$ estimate provides support for the neoclassical growth model and facilitates our interpretation of human capital types as aiding in the adoption and use of existing technologies. The same applies to the 32 individual U.S. states. This interpretation holds that human capital accumulation, if contributing positively to economic growth, does not do so by increasing the long-run, balanced growth rate. Rather, human capital allows for a given county to more effectively obtain, install and apply existing technologies. Despite not affecting the balanced growth rate, such affects are still important because they speak to how quickly poor counties can catch up to their wealthier counterparts.

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[14] In addition, we analyze the effect of a variable measuring the percent of a county's population employed in education services on growth (see section 6).

[15] Following Evans (1997b, footnote 17, p.16), we use $c = 1 - (1 + T\beta)^{\frac{1}{T}}$ to compute the asymptotic rate of convergence. The confidence intervals (in parentheses) are obtained in two steps. First, we obtain end points of the $\beta$ confidence intervals by computing $\beta \pm (1.96 \times s.e.)$, where $s.e.$ is the standard error associated with the $\beta$ estimate. Next, these endpoints are plugged into $c = 1 - (1 + T\beta)^{\frac{1}{T}}$. If the low value of the confidence interval is less than $-T^{-1}$, the higher value is set equal to 1. It is clear from the above that the confidence intervals computed this way may be asymmetric around the point estimates. As **Figure 1** indicates, this is indeed the case in our data.

The convergence rate estimates in **Table 3** provide a point of reference demonstrating that quantitative differences that arise from using the consistent 2SLS technique rather than OLS. For the full sample of 3,058 counties the 2SLS point estimate of the conditional convergence rate is 6.82 percent and is significant at the 1 percent level. This is compared to 2.37 percent using the inconsistent OLS method (also significant at the 1 percent level). The OLS 2.37 percent is similar to results that Barro and Sala-i-Martin (1992), Mankiw et al (1992), and Sala-i-Martin (1996) report. Sala-i-Martin (1996) has noted that a roughly 2 percent convergence rate is so commonly found in international, inter-state and inter-regional growth regressions that it qualifies as a "mnemonic rule." The difference between the OLS and 2SLS estimate is nearly 300 percent. This suggests that OLS introduces substantial bias.

The difference is economically large. A 2.37 percent convergence rate implies the gap between the present per capita income level and the balanced growth path halves in 31 to 32 years, while a 6.82 percent rate implies the same in 12 to 13 years.

The basic finding that conditional convergence rates are higher than the 2 percent "mnemonic rule" of Sala-i-Martin (1996) holds when examining 32 states as economies in and of themselves. **Figure 1** presents confidence intervals as vertical bars (that include the point estimates). The 2 percent rule is represented by a horizontal line. Every point estimate is above 2 percent, and the average point estimate is 8.1 percent. For one fourth (8) of the states the point estimate is above 10 percent.[16] Considering the 95 percent confidence intervals, we find that only 3 states have a lower bound of the confidence interval not greater than 2 percent (California, Iowa, and South Dakota all bottom out at 1.8 percent). These results are encouraging for laggard counties in the limited sense that, *given proper policies/conditions to induce and support balanced growth paths similar to leader counties*, the laggard counties can approach their balanced growth paths relatively quickly. Human capital levels represent part of those conditions, and studying their contributions provides policy-makers insights into what constitutes improvements in those conditions.

[16] It is worth noting that a 10 percent convergence rate implies that the distance from the balanced growth path is halved within 10 years.

## 5. Analysis of Human Capital Coefficients

As **Table 1** indicates, our data include four different variables measuring educational attainment within U.S. counties: the percent of the population with (a) 9-11 years of education and no more, (b) a high school diploma and no more, (c) some college education but less than a bachelor degree, and (d) a bachelor degree and/or higher degrees.[17] **Table 4** reports the 2SLS coefficient estimates for these four educational attainment variables for the full sample and within-state samples.

We first consider the percent of the population with at least 9 years of education, but less than a high school (or its equivalent) degree. For the full sample the coefficient is –0.0221 and is significant at the 1 percent level. This seems sensible. It implies that the greater percentage of an economy's population without the remedial mathematics, writing and communications skills – as well as the minimum personal discipline and social behavior – necessary to obtain a high school diploma, the lower the economy's balanced growth path.

The significant negative estimated effect also brings to the fore the danger of interpreting years of schooling as a monotonic, linear measure of homogenous human capital accumulation. In fact, some years of schooling may not even be indicative of human capital at all. Mankiw (1997, p.106) notes that "[S]econdary-school [high-school] enrollment represents a decision between work and education. By contrast, a 7-year-old not at school might be home with a parent. This time may at least represent a form of home schooling [and in general] primary-school enrollment might contain little information about human capital accumulation." Mankiw is referring to enrollment, rather than attainment measures, but his point remains: opportunity cost is the natural measure of human capital and the opportunity cost to the first 9-11 years of education is often nil.

Passing that threshold, the coefficient for the population achieving, but not surpassing, a high school diploma has a point estimate of 0.0097, also significant at the 1 percent level, for the full sample. Again, one can easily make the argument that the

[17] For the remaining four variables (for public and private elementary schools and nurseries) we get mixed results in the full sample in terms of statistical significance. Although two of them have statistically significant estimated coefficient values, none of the coefficients represent economically significant effects. The point estimates of all coefficients for the full sample are zero at four-digit precision.

completion of the high-school degree (the last two years of which are non-compulsory in most cases and apply to individuals old enough to join the labor force) has a positive opportunity cost and therefore represents a positive investment in human capital.

More surprisingly, for the full sample the coefficient point estimate is –0.0025 for the percent of the population with some college education but not enough for a bachelor degree. However, this estimate is not statistically different from zero. Compare this to the coefficient on the percent of the population with a bachelor degree or more: 0.0732 and significant at the 1 percent level. This point estimate, as well, dwarfs that of the high-school variable coefficient. A possible interpretation of this result again concerns opportunity cost. College education ostensibly involves a benefit in the form of increased skills/productivity for the individual, but it also involves a cost in the form of foregone wages. The results may imply that college education of at least 4 years represents (on average) a positive net return to individuals, while the net return on a 2-year degree is questionable.

Of course, the immediate response to the above is to ask: But then why do individuals go to college and not pursue bachelor degrees to begin with? Straightforward explanations include that the net return is positive but too small to be statistically identified and that individuals consistently overestimate the return. The first of these is a dead-end for this analysis, and the second is not appealing if we wish to maintain an assumption of some basic rationality on the part of agents. This does not rule out either of these explanations, but another explanation exists that is plausible and some evidence exists for: agents do not bear the full opportunity cost. Kane and Rouse (1995) and Surette (1997) both report that the estimated return to 2-year degrees is positive and equals about 4-6 percent and 7-10 percent respectively. However, these studies measure private return and not social return. They examine individuals' costs (tuition paid, wages forgone, experience forgone, etc.) and benefits (wage premiums). On the other hand, Kane and Rouse (p.600n) note that "Twenty percent of Federal Pell Grants, 10 percent of Guaranteed Student Loans, and over 20 percent of state expenditures for postsecondary education, go to community colleges." Our findings may be detecting that when the full opportunity cost is accounted for, the social return is nil.

Besides heterogeneity in the estimated effects of different types/levels of human capital accumulation, in all four of these categories of educational attainment we also find significant heterogeneity – sometimes qualitatively, sometimes only quantitatively, and in some cases both qualitatively and quantitatively – within categories across different states. In the case of the less than high school degree attainment, there are only 6 statistically significant (10 percent level or better) within-state coefficient estimates. These are evenly split as far as sign is concerned. They range from –0.0904 (South Dakota, 1 percent level) to 0.1171 (Colorado, 5 percent level). (These point estimates and their 95 percent confidence intervals are presented in **Figure 2**.) This heterogeneity is interesting. If the above interpretation we offered for the negative full sample coefficient (significant at the 1 percent level) is convincing, why would there be some individual state economies where having a larger percent of the population not obtaining a high school diploma be conducive to economic growth?

One potential explanation concerns compulsory education laws. The story could run two ways. Stronger (in terms of years required) laws might be associated with positive coefficients. The variable may include many people who would have had no high school education at all, given their druthers, and benefited by being forced to pick up some remedial math and verbal skills. On the other hand, stronger laws might be negatively associated with low coefficient estimates because of the opportunity cost forced on rather-be-truant individuals and the direct cost being incurred by the school system to deal with them. If these individuals are students being pushed through the school system (which is costly) while never actually receiving/accepting the benefits of education, they also forego the productive opportunities available in the meanwhile. However, neither of these stories is suggested by the data. Each of the 6 states included in **Figure 2** has roughly similar age spans of compulsion: 7 to 16 (Alabama, Colorado, Illinois and North Carolina), 6 to 16 (South Dakota), or 6 to 18 (Texas) years old.[18] There is no apparent correlation between these small differences and the coefficient estimates.

[18] These laws are from a report by the U.S. Department of Education (2001a), except for the Colorado law, which comes from the Colorado Department of Education.

Heterogeneity also exists across the significant high school diploma variable estimates (**Figure 3**). Of the 8 coefficient estimates significant at the 10 percent level or better, 2 of them are negative (Mississippi and Ohio) and 1 has a 95 percent confidence interval entirely in the negative range (Mississippi). However, among the 6 coefficients with positive point estimates there is no statistically significant difference between them.

One straightforward potential explanation for the existing heterogeneity is simply that school systems are simply better in some states than others.[19] This hypothesis can be informally tested by comparing average scholastic aptitude test (SAT) scores from the states with negative coefficient estimates to those with positive coefficient estimates. **Figures 4a**, **4b** and **4c** plot total, math and verbal average SAT scores for the 1998-1999 school year, respectively, for the 8 states included in **Figure 3**. Indeed, Ohio has both the lowest math and verbal average score (and, of course, total as well). However, Mississippi – with the only coefficient negative and significant at the 5 percent level – has SAT average scores neither exceptionally high nor low relative to the other seven states. Some school systems simply being better than others does not appear to be a satisfying explanation for the heterogeneity.[20]

No statistically significant heterogeneity can be detected among coefficients for the some college variable. This is shown in **Figure 5**. In the first place, for only 5 states is the coefficient statistically different from zero at the 10 percent level. Furthermore, the confidence intervals are all overlapping. Still, it should be noted that every point estimate shown is positive.

We find the same for the bachelor degree or more variable (**Figure 6**). Although we cannot distinguish the coefficient estimates for the 10 state coefficients significant at the 10 percent level, a full 9 of these 10 are significantly positive at the 5 percent level. In the case of the college education variable coefficients, in general, we cannot detect any statistically significant heterogeneity across U.S. states. The only statement we can make concerns homogeneity: the effect on a growth path of the percent of the population attaining four years of college education is positive uniformly across U.S. states.

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[19] Over the 1999-2000 school year private schools accounted for only 12 percent of elementary and secondary students in the U.S. (U.S. Department of Education (1999-2000)).

[20] The SAT score test of the hypothesis, however, relies on an assumption that the predominant portion of the population with high school degrees obtained their high school degrees in the considered state. For individual states, this seems *a priori* plausible but not certain.

## 6. Human Capital Fosters Growth. Providing It Does *Not*?

Our data set also includes county-level measures of the percent of a county's population employed in education services. While the results of educational attainment above are different across individual states and types/levels of attainment, the overall picture still would suggest that the provision of education has a positive, or at worst insignificant effect on economic growth. We find to the contrary.

The percent of the population providing education services is negatively correlated with economic growth in the full sample (point estimate -0.0334 and significant at the 1 percent level). Furthermore, no statistically significant qualitative heterogeneity is detected across states. For the 6 states with coefficient estimates significant at the 10 percent level or better, each and every point estimate is negative.

Why does human capital appear to foster growth while the provision of it does not? Perhaps the benefits of education provided in a given county are not internalized by the county itself. For example, we find a positive partial correlation between four-year college or higher educational attainment and economic growth, but the correlation is silent as to where the education was attained. Individuals may attend college or university where human capital is relatively easy to accumulate, and then move to other counties as they join the workforce. In Higgins et al (2003) we find that the negative correlation between education service provision and growth is particularly strong in metro counties. This is consistent with an externality argument insofar as a large proportion of colleges and universities are in metro areas, and many students leave the metro areas upon graduation. Indeed the estimated partial correlation is insignificant when the sample only includes non-metro counties.

Another explanation is bureaucratic overexpansion of the public school systems. This hypothesis is frequently entertained in the popular media and is explored by Marlow (2001) in the California primary and secondary school districts. However, Marlow finds that an increase in the number of teachers has no statistically significant effect on SAT scores or dropout rates while an increase in the size of administrative staff *increases* the SAT scores and *decreases* the dropout rates.

## 7. Conclusions

We use county-level data to study the role of different types of human capital accumulation in U.S. growth determination. The data includes over 3,000 cross-sectional observations and 39 demographic control variables. The large number of observations provides enough degrees of freedom to obtain estimates for the U.S. as a whole and 32 states in and of themselves. The data contains measures of educational attainment for four distinct categories: (a) 9 to 11 years, (b) high school diploma, (c) some college and (d) bachelor degree or more. These variables represent human capital stocks for each and every county.

Using a consistent two stage least squares estimation procedure, we find that (i) the percentage of a county's population with less than a high school education is negatively correlated with economic growth, (ii) the percentage obtaining a high school diploma but no more is positively correlated with economic growth, (iii) the percentage obtaining only some college education has no clear relationship with economic growth, but (iv) the percentage that obtains a bachelor degree or more is positively correlated with economic growth.. Further, we find that (v) there is significant qualitative heterogeneity in estimated coefficients across states for the 9 to 11 years and high school diploma categories but (vi) no qualitative heterogeneity for the college level categories.

The most consistent and significant conclusion across samples is that the percent of a county's population obtaining a bachelor degree or higher level of college education has a positive relationship with economic growth. Oddly enough, despite findings (ii), (iv) and (vi) above, we find that the percentage of a county's population employed in educational services is negatively correlated with economic growth.

For econometric estimation of growth equations we employ the neoclassical specification, which enables us to use the sign of the estimated coefficient on the initial income level as a discriminating test between the validity of the neoclassical growth model against the alternative of the endogenous growth model. We find that this coefficient is negative and significant for the full U.S. sample. In addition, we find that it is negative also for every individual state sample where the value is statistically significant. Thus, the data support the neoclassical growth model, which implies that high levels of human capital accumulation are conducive to the adoption and application of available technologies, and that this represents a positive contribution to economic growth via a higher balanced growth path.

**Data Appendix: Measurement of Per Capita Income**

Because of the critical importance of the income variable for the study of growth and convergence, we want to address its measurement in some detail. Two options were available to us for the construction of the county-level per capita income variable: (1) Census Bureau database, and (2) BEA-REIS database.

Income information collected by the Census Bureau for states and counties is prepared decennially from the "long-form" sample conducted as part of the overall population census (BEA, 1994). This money income information is based on the self-reported values by Census Survey respondents. An advantage of the Census Bureau's data is that they are reported and recorded by place of residence. These data, however, are available only for the "benchmark" years, i.e., the years in which the decennial Census survey is conducted.

The second source for this data, and the one chosen for this project, is personal income as measured by the Bureau of Economic Analysis (BEA).[21] The definitions that are used for the components of personal income for the county estimates are essentially the same as those used for the national estimates. For example, the BEA defines "personal income" as the sum of wage and salary disbursements, other labor income, proprietors' income (with inventory valuation and capital consumption adjustments), rental income (with capital consumption adjustment), personal dividend income and personal interest income. (BEA, 1994) "Wage and salary disbursements' are measurements of pre-tax income paid to employees. "Other labor income" consists of payments by employers to employee benefit plans. "Proprietors' income" is divided into two separate components—farm and non-farm. Per capita income is defined as the ratio of this personal income measure to the population of an area.

The BEA's estimates of personal income reflect the revised national estimates of personal income that resulted from the 1991 comprehensive revision and the 1992 and 1993 annual revisions of the national income and product accounts. The revised national estimates were incorporated into the local area estimates of personal income as part of a

[21] The data and their measurement methods are described in detail in "Local Area Personal Income, 1969–1992" published by the BEA under the Regional Accounts Data, February 2, 2001.

comprehensive revision in May 1993. In addition, the estimates incorporate source data that were not available in time to be used in the comprehensive revisions.[22]

The BEA compiles data from several different sources in order to derive this personal income measure. Some of the data used to prepare the components of personal income are reported and recorded by place of work rather than place of residence. Therefore, the initial estimates of these components are on a place-of-work basis. Consequently, these initial place-of-work estimates are adjusted so that they will be on a place-of-residence basis and so that the income of the recipients whose place of residence differs from their place of work will be correctly assigned to their county of residence.

As a result, a place of residence adjustment is made to the data. This adjustment is made for inter-county commuters and border workers utilizing journey-to-work (JTW) data collected by Census. For the county estimates, the income of individuals who commute between counties is important in every multi-county metropolitan area and in many non-metropolitan areas. The residence adjustment estimate for a county is calculated as the total inflows of the income subject to adjustment to county $i$ from county $j$ minus the total outflows of the income subject to adjustment from county $i$ to county $j$. The estimates of the inflow and outflow data are prepared at the Standard Industrial Classification (SIC) level and are calculated from the JTW data on the number of wage and salary workers and on their average wages by county of work for each county of residence from the Population Census.

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[22] For details of these revisions, see "Local Area Personal Income: Estimates for 1990–92 and Revisions to the Estimates for 1981–91," *Survey of Current Business* 74 (April 1994), 127–129.

**Econometric Appendix**

The method of ordinary least squares (OLS) could be used to infer the values of $\beta$ and $\gamma$ in equation (3). However, Evans (1997b) states that the OLS estimates obtained from (3) are unlikely to be consistent.[23] In order to demonstrate this inconsistency, Evans first specifies a general autoregressive moving average (ARMA) data-generating process for $y_{nt}$:

(1A) $$y_{nt} - a_t = \delta_n + \lambda_n(y_{n,t-1} - a_{t-1}) + \sum_{i=1}^{q} \theta_{ni}\varepsilon_{n,t-i}$$

with

(2A) $$\delta_n = \kappa + \xi_n' x_n + \omega_n$$

where $\varepsilon_{nt}$ is a zero-mean, covariance stationary error process independently distributed over time and across economies. The error term, $\varepsilon_{nt}$, is uncorrelated with $x_n$, $\lambda_n$ is an autoregressive parameter which lies on $(0,1]$, and $\theta_{n0}...\theta_{nq}$ satisfy the restriction $\theta_{n0} = 1$. As such, $y_{nt} - a_t$ will also have an autoregressive representation and will be covariance stationary if $\lambda_n$<1 or difference stationary if $\lambda_n = 1$. The common time-specific effect experienced by every economy is represented by the term $a_t$. Evans assumes that $\Delta a_t$ is covariance stationary and independent of $\varepsilon_{nt}$.

The common trend $a_t$ for all the $y$ variables will be the sole catalyst of economic growth in all economies if $\lambda_n$<1. In this case, growth is exogenous and economies would follow a balanced-growth path. If $\lambda_n$=1, on the other hand, then economy $n$ will grow endogenously since $y_{nt}$ diverges from $a_t$ and the $y$ variables of all remaining economies. The parameter $\delta_n$ controls for the relative height of economy $n$'s balanced growth path if all the $\lambda$s are less than one. If $\lambda_n = 1$, then $\delta_n$ controls for economy $n$'s relative growth rate. The error term $\omega_n$ measures the portion of $\delta_n$ that is not explained

[23] This section borrows heavily from Evans (1997b), which can be consulted for further details.

by $x_n$. This error term is assumed to be uncorrelated with $x_n$. The inequality $\lambda_n$<1 will hold for an economy described by the neoclassical growth model.

Solving equation (1A) backward from year *T* to year 0, substituting from equation (2A), and rearranging produces

(3A)
$$g_n = \alpha_n + \beta_n y_{n0} + \gamma_n' x_n - \frac{\beta_n \omega_n}{1-\gamma_n} + \frac{1}{T}\sum_{i=0}^{T-1} \lambda_n^i \left( \sum_{j=0}^{\min[i,q]} \lambda_n^{-j} \theta_{nj} \right) \varepsilon_{n,T-i}$$
$$+ \left( \frac{\lambda_n^T}{T} \right) \sum_{i=0}^{q-1} \lambda_n^i \left( \sum_{j=i+1}^{q} \lambda_n^{-j} \theta_{nj} \right) \varepsilon_{n,-i}$$

where $\beta_n = \frac{\lambda_n^T - 1}{T}$, $\gamma_n = \frac{-\beta_n \xi_n}{1-\lambda_n}$, and $\alpha_n = \frac{a_T - a_0}{T - \beta_n \left( \frac{a_0 + \kappa}{1-\lambda_n} \right)}$. If $\beta_n < 0$, then economy $n$ grows exogenously $(\lambda_n < 1)$. On the other hand, if $\beta_n = 0$, then economy $n$ grows endogenously $(\lambda_n = 1)$.

Now consider a special case in which every intercept $\delta_n$ is completely explained by the county characteristics included in $x_n$ $(\omega_n = 0, \forall n)$ and every series $y_{nt} - a_t$ is a first-order auto-regression $(q = 0)$. Under these restrictions equation (3A) reduces to:

(4A)
$$g_n = \alpha_n + \beta_n y_{n0} + \gamma_n' x_n + \frac{1}{T}\sum_{i=0}^{T-1} \lambda_n^i \varepsilon_{n,T-i}$$

The estimator for $\hat{\beta}$ can then be obtained in two steps. First, regress $y_{n0}$ on an intercept and $x_n$ to obtain the residual $r_n$ and then regress $g_n$ on $r_n$. (This is simply the OLS estimator of $\beta$.) Each term in $\frac{1}{T}\sum_{i=0}^{T-1} \lambda_n^i \varepsilon_{n,T-i}$ is uncorrelated with the intercept, $y_n$, $x_n$ and the residual $r_n$. As a result, one has

(5A) $$\operatorname*{plim}_{N\to\infty}\hat{\beta} = \frac{\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}\alpha_n r_n + \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}\beta_n r_n y_n + \operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}\gamma'_n r_n x_n}{\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}r_n^2}$$

Making further assumptions that $\alpha_n$ is uncorrelated with $r_n$, $\beta_n$ is uncorrelated with $r_n y_n$, and $\gamma_n$ is uncorrelated with $r_n x_n$, equation (5A) leads to

(6A) $$\operatorname*{plim}_{N\to\infty}\hat{\beta} = \frac{\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}\beta_n r_n^2}{\operatorname*{plim}_{N\to\infty}\frac{1}{N}\sum_{n=1}^{N}r_n^2}$$

The probability limit of the OLS estimator is then a weighted average of the economy specific $\beta_n$s. It is a consistent estimator of that weighted average.[24]

But what if the assumption that every intercept $\delta_n$ is completely explained by $x_n$ and also the assumption that every series $y_{nt} - a_t$ is a first-order auto-regression, are relaxed? Relaxing these assumptions, and imposing the additional restriction that the $\lambda$s and $\xi$s and, as a result, the $\beta$s and $\gamma$s are identical across all economies (for the simplicity of the exposition), (3A) can be re-written as

(7A) $$g_n = \alpha + \beta y_{n0} + \gamma' x_n - \frac{\beta\omega_n}{1-\gamma} + \frac{1}{T}\sum_{i=0}^{T-1}\lambda^i\left(\sum_{j=0}^{\min[i,q]}\lambda^{-j}\theta_{nj}\right)\varepsilon_{n,T-i} + \left(\frac{\lambda^T}{T}\right)\sum_{i=0}^{q-1}\lambda^i\left(\sum_{j=i+1}^{q}\lambda^{-j}\theta_{nj}\right)\varepsilon_{n,-i}$$

[24] Strictly speaking, even for this restrictive case, an OLS estimate less than unity does not mean that all the economies in the sample conform to the neoclassical growth model. Rather, it would mean that enough economies conform, so that the weighted average is less than unity. It would mean, therefore, that exogenous growth is the predominant case across the sample.

where $\beta = \frac{\lambda^T - 1}{T}$, $\gamma = \frac{-\beta\xi}{1-\lambda}$, and $\alpha = \frac{a_T - a_0}{T - \beta\left(\frac{a_0 + \kappa}{1-\lambda}\right)}$. Applying the same steps to equation (6A) yields

(8A) $$\underset{N\to\infty}{p\lim}\,\hat{\beta} = \beta + \frac{(\Phi + \Psi)}{\underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N} r_n^2}$$

where $\Phi = \frac{\lambda^T}{T}\underset{N\to\infty}{p\lim}\frac{I}{N}\sum_{n=1}^{N}\left[\sum_{i=0}^{q-1}\lambda^i\left(\sum \lambda^{-j}\theta_{n,j+i+1}\right)r_n\varepsilon_{n,-i}\right]$ and $\Psi = -\frac{\beta}{1-\lambda}\underset{N\to\infty}{p\lim}\frac{1}{N}\sum r_n\omega_n$.

As a result, equation (8A) implies that $\underset{N\to\infty}{p\lim}\,\hat{\beta}$ differs from $\beta$ if *either* $q > 0$ ($y_{nt} - a_t$ is not a first-order AR process) or the cross-sectional variance of $\omega_n$ is positive (not all cross-sectional heterogeneity is accounted for). In other words, the OLS estimator is inconsistent unless (a) the log of income per capita has an identical first-order AR representation across economies, and (b) all cross-section heterogeneity is controlled for.

Evans shows that the resulting bias from $q > 0$ is likely to be negligible in practice but the bias resulting from a positive cross-sectional variance for $\omega_n$ can be substantial. This is essentially an omitted variable bias. Evans demonstrates that

(9A) $$\underset{N\to\infty}{p\lim}\hat{\beta} = \left[\frac{\text{var}(y \mid x,\omega)}{\text{var}(y \mid x)}\right]\beta$$

and

(10A) $$\underset{N\to\infty}{p\lim}\hat{\gamma} = \left[\frac{\text{var}(y \mid x,\omega)}{\text{var}(y \mid x)}\right]\gamma.$$

The bracketed portions in equations (9A) and (10A) are the ratio of the cross-sectional variance of $y_{n0}$ conditional on both $x_n$ and $\omega_n$ to the cross-sectional variance of $y_{n0}$ on

$x_n$. As such, $\hat{\beta}$ and $\hat{\gamma}$ will be biased towards zero unless the $xs$ are able to control for a large portion of the cross-economy variation in the $ys$.

The intuition here is that if a large portion of the growth of per capita income is explained by variables left out of the OLS regression, then the estimate of the convergence effect will be biased. In general, omitted variable bias can be either positive or negative. However, in this case, theoretically, the bias is negative. Evans (1997b, Tables on p. 11 and p. 15) estimates $\beta$ for Mankiw, et al.'s (1992) international data using both the OLS, which yields inconsistent estimates, and the 2SLS approach (as outlined in section 2), which yields consistent estimates of both $\beta$ and $\gamma$. He finds that the 2SLS estimate implies a conditional convergence rate between 4 to 5 times as large as the OLS estimate. The bias produced by the OLS in this case, therefore, is substantial.

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**Table 1: Variable Definitions and their Source**

| Variable | Definition | Period | Source |
|---|---|---|---|
| Income | Per Capita Personal Income (excluding transfer payments) | 1969–1998 | BEA[25] |
| Land Area | Land Area in $km^2$ | 1970-1990 | Census[26] |
| Water Area | Water Area in $km^2$ | 1970-1990 | Census |
| Age: 5-13 years | Percent of 5–13 year olds in the population | 1970-1990 | Census |
| Age: 14-17 years | Percent of 14–17 year olds in the population | 1970-1990 | Census |
| Age: 18-64 years | Percent of 18–64 year olds in the population | 1970-1990 | Census |
| Age: 65+ | Percent of 65+ olds | 1970-1990 | Census |
| Blacks | Percent of Blacks | 1970-1990 | Census |
| Hispanic | Percent of Hispanics | 1970-1990 | Census |
| Education: 9-11 years | Percent of population with 11 years education or less | 1970-1990 | Census |
| Education: H.S. diploma | Percent of population with high school diploma | 1970-1990 | Census |
| Education: Some college | Percent of population with some college education | 1970-1990 | Census |
| Education: Bachelor + | Percent of population with bachelor degree or above | 1970-1990 | Census |
| Education: Public elementary | Number of students enrolled in public elementary schools | 1970-1990 | Census |
| Education: Public nursery | Number of students enrolled in public nurseries | 1970-1990 | Census |
| Education: Private elementary | Number of students enrolled in private elementary schools | 1970-1990 | Census |
| Education: Private nursery | Number of students enrolled in private nurseries | 1970-1990 | Census |
| Housing | Median house value | 1970-1990 | Census |
| Federal government employment | Percent of population employed by the federal government in the county | 1969-1998 | BEA |
| State government employment | Percent of population employed by the state government in the county | 1969-1998 | BEA |
| Local government employment | Percent of population employed by the local government in the county | 1969-1998 | BEA |
| Self-employment | Percent of population self-employed | 1970-1990 | Census |
| Agriculture | Percent of population employed in agriculture | 1970-1990 | Census |
| Communications | Percent of population employed in communications | 1970-1990 | Census |
| Construction | Percent of population employed in construction | 1970-1990 | Census |
| Finance, insurance & real estate | Percent of population employed in finance, insurance, and real estate | 1970-1990 | Census |
| Manufacturing: durables | Percent of population employed in Manufacturing of durables | 1970-1990 | Census |
| Manufacturing: non-durables | Percent of population employed in manufacturing of non-durables | 1970-1990 | Census |
| Mining | Percent of population employed in mining | 1970-1990 | Census |
| Retail | Percent of population employed in retail trade | 1970-1990 | Census |
| Business & repair services | Percent of population employed in business and repair services | 1970-1990 | Census |
| Educational services | Percent of population employed in education services | 1970-1990 | Census |
| Professional related services | Percent of population employed in professional services | 1970-1990 | Census |
| Health services | Percent of population employed in health services | 1970-1990 | Census |

[25] All BEA variables are available for each year from 1969-1998.
[26] Note, all Census variables are gathered from the 1970, 1980 & 1990 Census tapes. Values for 1969 were obtained via the interpolation method as discussed in the data section.

**Table 1: Variable Definitions and their Sources (Cont.)**

| | | | |
|---|---|---|---|
| Personal services | Percent of population employed in personal services | 1970-1990 | Census |
| Entertainment & recreational services | Percent of population employed in entertainment and recreational services | 1970-1990 | Census |
| Transportation | Percent of population employed in transportation | 1970-1990 | Census |
| Wholesale trade | Percent of population employed in wholesale trade | 1970-1990 | Census |
| Poverty | Percent of the population living at or below the poverty level | 1970-1990 | Census |
| Metro area, 1970 | Dummy Variable: 1 if the county was in a metro area in 1970, and 0 otherwise | 1970 | Census |

**Table 2: Analysis of Beta Values**

| State | Number of Counties | Unconditional | OLS | 2SLS |
|---|---|---|---|---|
| United States[27] | 3,058 | -0.0068 (15.88)* | -0.0174 (22.15)* | -0.0345 (24.19)* |
| Alabama | 67 | -0.0039 (1.56) | -0.0251 (2.38)** | -0.0334 (20.49)* |
| Arkansas | 74 | -0.0086 (3.20)* | -0.0267 (4.48)* | -0.0384 (22.08)* |
| California | 58 | 0.0218 (3.99)* | -0.0261 (2.50)** | -0.0235 (4.87)* |
| Colorado | 63 | -0.0041 (1.26) | -0.0134 (2.53)** | -0.0318 (13.41)* |
| Florida | 67 | 0.0026 (0.81) | -0.0190 (2.06)** | -0.0319 (14.98)* |
| Georgia | 159 | -0.0065 (3.09)* | -0.0171 (4.33)* | -0.0367 (36.46)* |
| Idaho | 44 | -0.0182 (3.66)* | -0.0403 (2.23)** | -0.0406 (10.03)* |
| Illinois | 102 | -0.0030 (1.41) | -0.0255 (5.46)* | -0.0281 (9.07)* |
| Indiana | 92 | 0.0004 (0.11) | -0.0061 (1.02) | -0.0299 (9.25)* |
| Iowa | 99 | -0.0069 (1.85)*** | -0.0288 (5.65)* | -0.0289 (4.75)* |
| Kansas | 106 | -0.0163 (7.84)* | -0.0286 (9.76)* | -0.0301 (12.18)* |
| Kentucky | 120 | -0.0043 (2.85)* | -0.0253 (6.11)* | -0.0354 (19.74)* |
| Louisiana | 64 | -0.0032 (1.22) | -0.0222 (3.83)* | -0.0413 (13.83)* |
| Michigan | 83 | 0.0056 (2.14)** | -0.0104 (1.36) | -0.0387 (16.52)* |
| Minnesota | 87 | -0.0056 (2.44)** | -0.0156 (2.85)* | -0.0260 (9.34)* |
| Mississippi | 82 | 0.0012 (0.43) | -0.0182 (2.05)** | -0.0448 (13.43)* |
| Missouri | 115 | -0.0038 (2.34)** | -0.0171 (3.78)* | -0.0455 (10.74)* |
| Montana | 56 | -0.0244 (5.31)* | -0.0229 (3.31)* | -0.0328 (9.14)* |
| New York | 62 | 0.0120 (4.45)* | 0.0129 (1.24) | -0.0264 (7.78)* |
| North Carolina | 100 | -0.0033 (1.47) | -0.0171 (3.32)* | -0.0467 (7.11)* |
| North Dakota | 53 | -0.0119 (1.85)*** | -0.0279 (3.29)* | -0.0594 (4.79)* |
| Ohio | 88 | 0.0047 (1.83)*** | -0.0136 (1.87)*** | -0.0274 (7.68)* |
| Oklahoma | 77 | -0.0123 (6.49)* | -0.0248 (3.95)* | -0.0387 (22.11)* |
| Pennsylvania | 67 | 0.0038 (1.31) | -0.0176 (2.53)** | -0.0312 (9.01)* |
| South Carolina | 46 | 0.0014 (0.53) | -0.0118 (0.62) | -0.0336 (5.97)* |
| South Dakota | 66 | 0.0003 (0.06) | -0.0193 (2.39)** | -0.0265 (4.77)* |
| Tennessee | 97 | -0.0002 (0.07) | -0.0199 (3.55)* | -0.0392 (15.21)* |
| Texas | 254 | -0.0086 (5.09)* | -0.0211 (8.10)* | -0.0356 (15.18)* |
| Virginia | 84 | 0.0016 (0.62) | -0.0045 (0.69) | -0.0348 (15.81)* |
| Washington | 39 | -0.0129 (1.96)** | -0.0349 (1.09) | -0.0327 (9.29)* |
| West Virginia | 55 | -0.0053 (1.81)*** | 0.0043 (0.43) | -0.0336 (15.49)* |
| Wisconsin | 70 | -0.0009 (0.37) | -0.0191 (3.08)* | -0.0240 (6.83)* |

*t*-statistics are reported in parentheses

* significant at 1% level
** significant at 5% level
*** significant at 10% level

[27] See Higgins, Levy and Young (2002).

**Table 3 Asymptotic Convergence Rates – Point Estimates & 95% Confidence Intervals**

| State | Number of Counties | OLS Estimates & 95% C.I. [28] | 2SLS Estimates & C.I. |
|---|---|---|---|
| United States[29] | 3,058 | 0.0237 (0.0208, 0.0267) | 0.0682 (0.0544, 0.0911) |
| Alabama | 67 | 0.0424 (0.0036, 0.1080) | 0.0931 (0.0492, 0.1466) |
| Arkansas | 74 | 0.0479 (0.0166, 0.1098) | 0.0738 (0.0570, 0.1363) |
| California | 58 | 0.0457 (0.0046, 0.1249) | 0.0375 (0.0178, 0.0868) |
| Colorado | 63 | 0.0166 (0.0031, 0.0384) | 0.0759 (0.0426, 0.1009) |
| Florida | 67 | 0.0268 (0.0010, 0.1109) | 0.0767 (0.0480, 0.1174) |
| Georgia | 159 | 0.0230 (0.0109, 0.0413) | 0.1043 (0.0699, 0.1142) |
| Idaho | 44 | 0.0892 (0.0021, 0.1566) | 0.0913 (0.0471, 0.1145) |
| Illinois | 102 | 0.0434 (0.0213, 0.1168) | 0.0537 (0.0337, 0.1062) |
| Indiana | 92 | 0.0067 (-0.0054, 0.0245) | 0.0622 (0.0354, 0.1221) |
| Iowa | 99 | 0.0570 (0.0224, 0.1176) | 0.0574 (0.0175, 0.0954) |
| Kansas | 106 | 0.0560 (0.0360, 0.1086) | 0.0639 (0.0434, 0.1228) |
| Kentucky | 120 | 0.0431 (0.0233, 0.0922) | 0.1054 (0.0561, 0.1160) |
| Louisiana | 64 | 0.0341 (0.0128, 0.0955) | 0.1555 (0.0989, 0.1940) |
| Michigan | 83 | 0.0121 (-0.0043, 0.0427) | 0.1152 (0.0536, 0.1659) |
| Minnesota | 87 | 0.0202 (0.0053, 0.0459) | 0.0454 (0.0305, 0.0719) |
| Mississippi | 82 | 0.0249 (0.0009, 0.1509) | 0.1405 (0.0455, 0.1923) |
| Missouri | 115 | 0.0230 (0.0094, 0.0452) | 0.0817 (0.0387, 0.1132) |
| Montana | 56 | 0.0359 (0.0099, 0.0996) | 0.0865 (0.0367, 0.1566) |
| New York | 62 | 0.0111 (-0.0238, 0.0284) | 0.0465 (0.0285, 0.0853) |
| North Carolina | 100 | 0.0228 (0.0078, 0.0491) | 0.1302 (0.0966, 0.1574) |
| North Dakota | 53 | 0.0528 (0.0103, 0.1247) | 0.0761 (0.0353, 0.1102) |
| Ohio | 88 | 0.0170 (-0.0005, 0.0520) | 0.0503 (0.0299, 0.1059) |
| Oklahoma | 77 | 0.0415 (0.0139, 0.1136) | 0.1152 (0.0574, 0.1437) |
| Pennsylvania | 67 | 0.0240 (0.0043, 0.0707) | 0.0705 (0.0291, 0.1099) |
| South Carolina | 46 | 0.0142 (-0.0147, 0.1259) | 0.0960 (0.0243, 0.1315) |
| South Dakota | 66 | 0.0274 (0.0036, 0.1391) | 0.0406 (0.0184, 0.1144) |
| Tennessee | 97 | 0.0287 (0.0102, 0.0689) | 0.0681 (0.0488, 0.1168) |
| Texas | 254 | 0.0312 (0.0208, 0.0458) | 0.1170 (0.0675, 0.1564) |
| Virginia | 84 | 0.0047 (-0.0074, 0.0227) | 0.0703 (0.0500, 0.1271) |
| Washington | 39 | 0.0518 (-.0119, 0.0971) | 0.0845 (0.0448, 0.1449) |
| West Virginia | 55 | 0.0040 (-0.0184, 0.0199) | 0.0634 (0.0466, 0.0972) |
| Wisconsin | 70 | 0.0270 (0.0077, 0.0716) | 0.0390 (0.0231, 0.0688) |

[28] Asymptotic convergence rates and 95% confidence intervals reported are for those estimates statistically different than zero in the 2SLS regressions.

[29] See Higgins, Levy and Young (2002) for full set of results for the United States.

**Table 4: Analysis of Education Variables**

| Region | 9-11 Years and No More | | High School Diploma | | Some College Education | | Bachelor Degree or Higher | |
|---|---|---|---|---|---|---|---|---|
| | 2SLS | 95% C.I. | 2SLS | 95% C.I. | 2SLS | 95% C.I. | 2SLS | 95% C.I. |
| United States | -0.0221 (6.21)* | (-0.0292, -0.0152) | 0.0097 (3.26)* | (0.0038, 0.0156) | -0.0025 (0.41) | (-0.0143, 0.0094) | 0.0732 (12.01)* | (0.0613, 0.0852) |
| Alabama | 0.0832 (2.07)** | (0.0015, 0.1649) | 0.0832 (2.07)** | (0.0014, 0.1649) | 0.1229 (1.41) | (-0.0538, 0.2997) | 0.0448 (0.77) | (-0.0741, 0.1639) |
| Arkansas | -0.0223 (0.73) | (-0.0844, 0.0397) | 0.1539 (0.49) | (-0.0478, 0.0786) | 0.0492 (0.75) | (-0.0832, 0.1818) | 0.1188 (1.56) | (-0.0346, 0.2723) |
| California | -0.0673 (1.02) | (-0.2041, 0.0694) | -0.0212 (0.60) | (-0.0941, 0.0515) | 0.0513 (0.77) | (-0.0857, 0.1884) | 0.1003 (2.36)* | (0.0126, 0.1880) |
| Colorado | 0.1171 (2.44)** | (0.0191, 0.2151) | 0.0654 (2.23)** | (0.0053, 0.1255) | 0.0600 (0.90) | (-0.0769, 0.1969) | 0.1178 (3.03)* | (0.0382, 0.1974) |
| Florida | -0.0045 (0.07) | (-0.1282, 0.1193) | 0.0649 (0.95) | (-0.0750, 0.2048) | 0.1813 (1.69)*** | (-0.0372, 0.3998) | 0.1094 (1.28) | (-0.0647, 0.2837) |
| Georgia | 0.0087 (0.58) | (-0.0210, 0.0384) | 0.0103 (0.60) | (-0.0240, 0.0447) | 0.0715 (1.77)*** | (-0.0084, 0.1515) | 0.0279 (0.90) | (-0.0335, 0.0894) |
| Idaho | 0.0612 (0.93) | (-0.0859, 0.2085) | 0.0893 (2.31)** | (0.0031, 0.1755) | -0.0052 (0.11) | (-0.1135, 0.1030) | 0.0656 (0.65) | (-0.1579, 0.2891) |
| Illinois | -0.0587 (3.22)* | (-0.0952, -0.0223) | -0.0149 (1.38) | (-0.0364, 0.0066) | 0.0280 (0.89) | (-0.0345, 0.0907) | 0.0495 (1.61) | (-0.0117, 0.1108) |
| Indiana | -0.0333 (1.31) | (-0.0842, 0.0175) | -0.0220 (1.37) | (-0.0542, 0.0102) | 0.1129 (2.09)** | (0.0045, 0.2214) | 0.0406 (0.82) | (-0.0584, 0.1396) |
| Iowa | -0.0314 (1.28) | (-0.0803, 0.0174) | -0.0003 (0.03) | (-0.0245, 0.0238) | 0.0157 (0.58) | (-0.0383, 0.0698) | -0.0369 (1.20) | (-0.0983, 0.0244) |
| Kansas | -0.0281 (1.34) | (-0.0697, 0.0135) | 0.0556 (4.49)* | (0.0309, 0.0804) | -0.0031 (0.16) | (-0.0414, 0.0351) | 0.0403 (1.54) | (-0.0118, 0.0925) |
| Kentucky | 0.0140 (0.51) | (-0.0410, 0.0692) | 0.0562 (3.07)* | (0.0198, 0.0925) | 0.0769 (1.77)*** | (-0.0096, 0.1635) | 0.0711 (1.55) | (-0.0202, 0.1625) |
| Louisiana | 0.0188 (0.73) | (-0.0340, 0.0717) | -0.0178 (0.86) | (-0.0600, 0.0243) | 0.0717 (1.19) | (-0.0509, 0.1943) | 0.0707 (1.19) | (-0.0508, 0.1922) |
| Michigan | -0.0428 (1.34) | (-0.1067, 0.0211) | -0.0187 (0.77) | (-0.0677, 0.0302) | -0.0079 (0.15) | (-0.1131, 0.0972) | 0.0873 (2.44)** | (0.0154, 0.1592) |
| Minnesota | -0.0142 (0.43) | (-0.0803, 0.0520) | 0.0053 (0.31) | (-0.0290, 0.0396) | 0.0441 (1.23) | (-0.0281, 0.1165) | 0.0273 (0.64) | (-0.0578, 0.1126) |
| Mississippi | 0.0095 (0.30) | (-0.0551, 0.0743) | -0.0950 (2.24)** | (-0.1804, -0.0095) | -0.0352 (0.57) | (-0.1595, 0.0891) | 0.0182 (0.25) | (-0.1294, 0.1659) |
| Missouri | -0.0226 (0.83) | (-0.0773, 0.0319) | 0.0187 (1.11) | (-0.0149, 0.0523) | -0.0271 (0.71) | (-0.1028, 0.0484) | 0.1255 (3.50)* | (0.0542, 0.1969) |
| Montana | -0.1081 (1.54) | (-0.2529, 0.0368) | -0.0028 (0.07) | (-0.0856, 0.0799) | 0.0100 (0.24) | (-0.0755, 0.0956) | 0.0085 (0.17) | (-0.0983, 0.1154) |
| New York | 0.0306 (0.68) | (-0.0616, 0.1229) | -0.0719 (1.51) | (-0.1697, 0.0258) | 0.0193 (0.26) | (-0.1324, 0.1712) | 0.1734 (3.31)* | (0.0661, 0.2807) |
| North Carolina | 0.0395 (1.85)*** | (-0.0031, 0.0821) | 0.0223 (1.07) | (-0.0193, 0.0641) | -0.0162 (0.34) | (-0.1125, 0.0800) | 0.1134 (3.02)* | (0.0384, 0.1883) |
| Ohio | 0.0171 (0.60) | (-0.0400, 0.0742) | -0.0317 (1.87)*** | (-0.0656, 0.0022) | 0.1305 (2.62)* | (0.0305, 0.2306) | 0.0691 (1.58) | (-0.0187, 0.1571) |
| Oklahoma | -0.0018 (0.05) | (-0.0769, 0.0732) | 0.0556 (2.43)** | (0.0095, 0.1017) | 0.0728 (1.54) | (-0.0226, 0.1683) | 0.0230 (0.59) | (-0.0553, 0.1014) |
| Pennsylvania | -0.0021 (0.07) | (-0.0626, 0.0584) | -0.0331 (1.59) | (-0.0754, 0.0091) | 0.0121 (0.20) | (-0.1105, 0.1348) | 0.2049 (4.32)* | (0.1085, 0.3014) |
| South Carolina | -0.0098 (0.20) | (-0.1160, 0.0962) | -0.1084 (1.48) | (-0.2676, 0.0508) | 0.1236 (0.66) | (-0.2876, 0.5355) | 0.0301 (0.17) | (-0.3684, 0.4249) |
| South Dakota | -0.0904 (2.58)* | (-0.1621, -0.0186) | 0.0181 (0.80) | (-0.0279, 0.0642) | 0.0352 (0.72) | (-0.0647, 0.1353) | -0.0811 (1.39) | (-0.1999, 0.0376) |
| Tennessee | 0.0093 (0.33) | (-0.0477, 0.0665) | 0.0077 (0.26) | (-0.0511, 0.0666) | -0.0673 (1.10) | (-0.1897, 0.0549) | 0.1732 (3.04)* | (0.0592, 0.2872) |
| Texas | -0.0594 (4.85)* | (-0.0836, -0.0353) | 0.0061 (0.45) | (-0.0208, 0.0330) | 0.0282 (1.28) | (-0.0153, 0.0717) | -0.0175 (0.70) | (-0.0667, 0.0315) |
| Virginia | 0.0128 (0.48) | (-0.0412, 0.0668) | 0.0157 (0.54) | (-0.0429, 0.0744) | -0.0211 (0.28) | (-0.1756, 0.1333) | 0.0961 (1.68)*** | (-0.0191, 0.2114) |
| Washington | 0.0307 (0.21) | (-0.3521, 0.4135) | 0.0146 (0.12) | (-0.2885, 0.3178) | 0.0199 (0.28) | (-0.1656, 0.2055) | 0.1531 (0.95) | (-0.2609, 0.5673) |
| West Virginia | 0.0470 (0.81) | (-0.0733, 0.1674) | -0.0223 (0.50) | (-0.1146, 0.0700) | -0.0134 (0.15) | (-0.2037, 0.1768) | 0.1089 (0.98) | (-0.1206, 0.3385) |
| Wisconsin | -0.0276 (0.95) | (-0.0855, 0.0308) | -0.0268 (1.62) | (-0.0605, 0.0067) | 0.0229 (0.71) | (-0.0424, 0.0884) | 0.0923 (2.56)** | (0.0195, 0.1652) |

t-statistics are reported in parentheses

* significant at 1% level
** significant at 5% level
*** significant at 10% level

**Figure 1:**
**95% Confidence Intervals and Point Estimates of Within-State Asymptotic Convergence Rates**

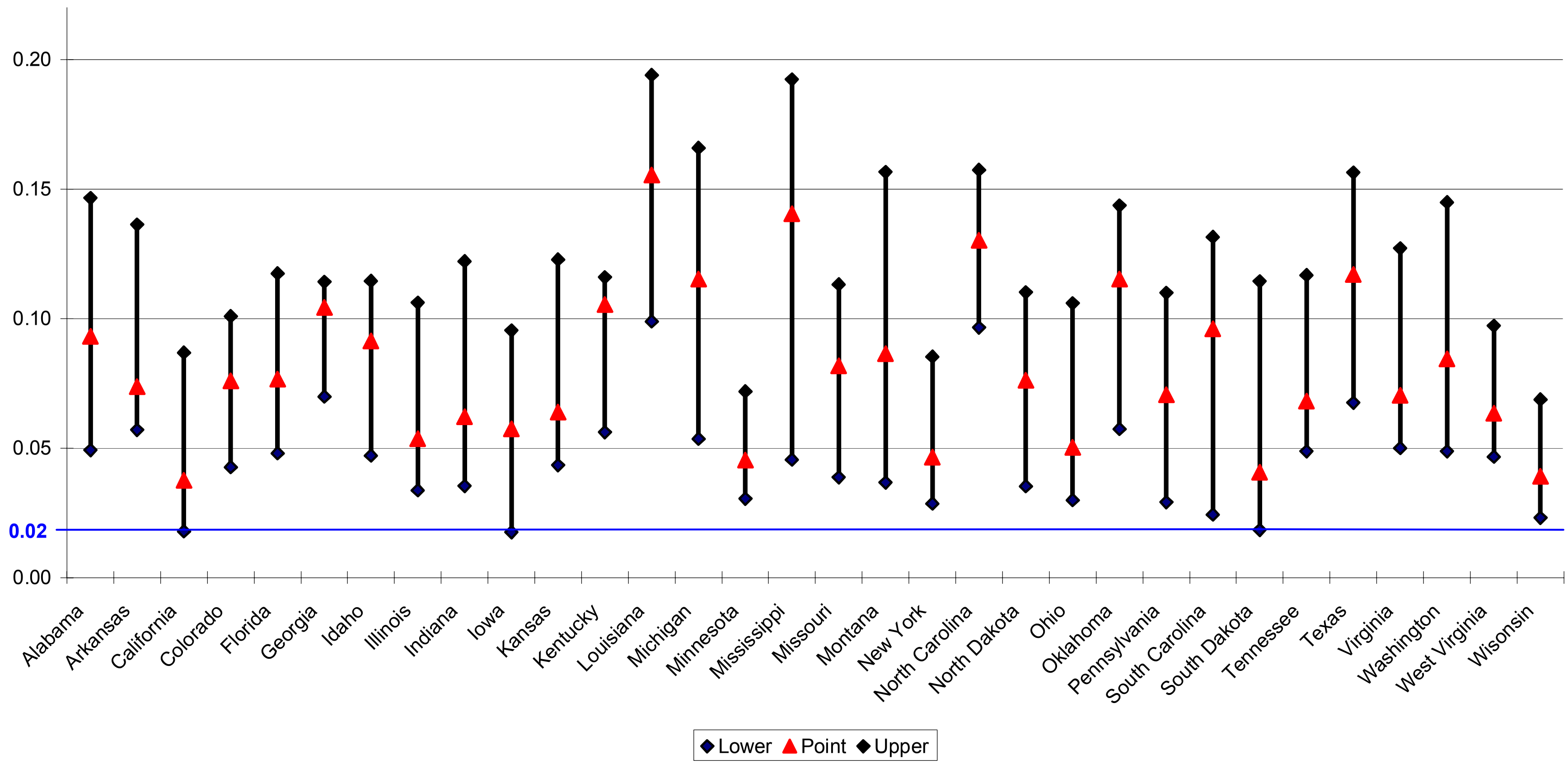

**Figure 2:**
**95% Confidence Intervals and Point Estimates of Within-State Education Regression Coefficients: 9-11 Years and No More**

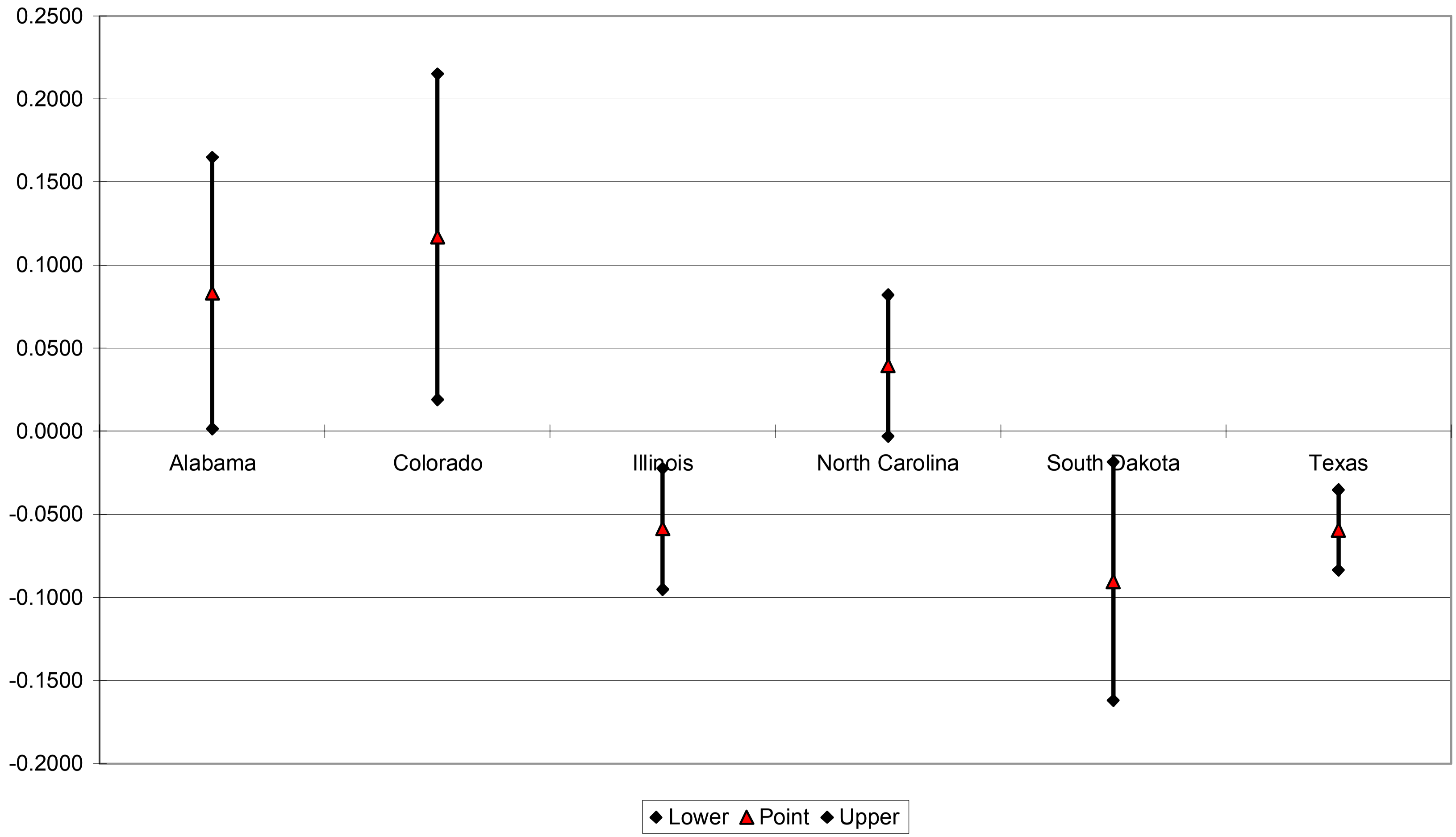

**Figure 3:**
**95% Confidence Intervals and Point Estimates of Within-State Education Regression Coefficents: High School Diploma**

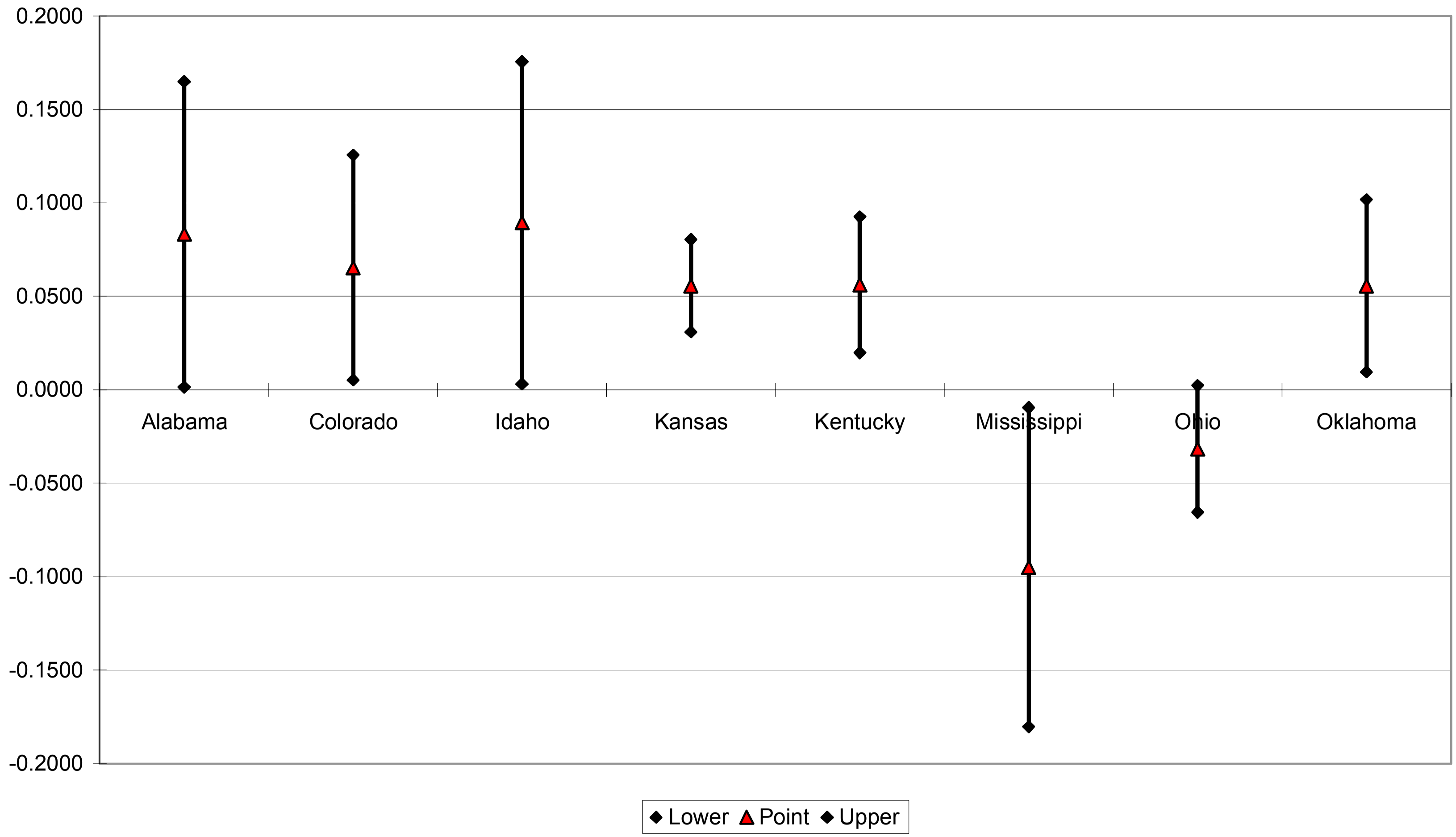

**Figure 4a:**
**1998-1999 Average Total SAT Scores Versus High School Diploma Coefficient Point Estimates**

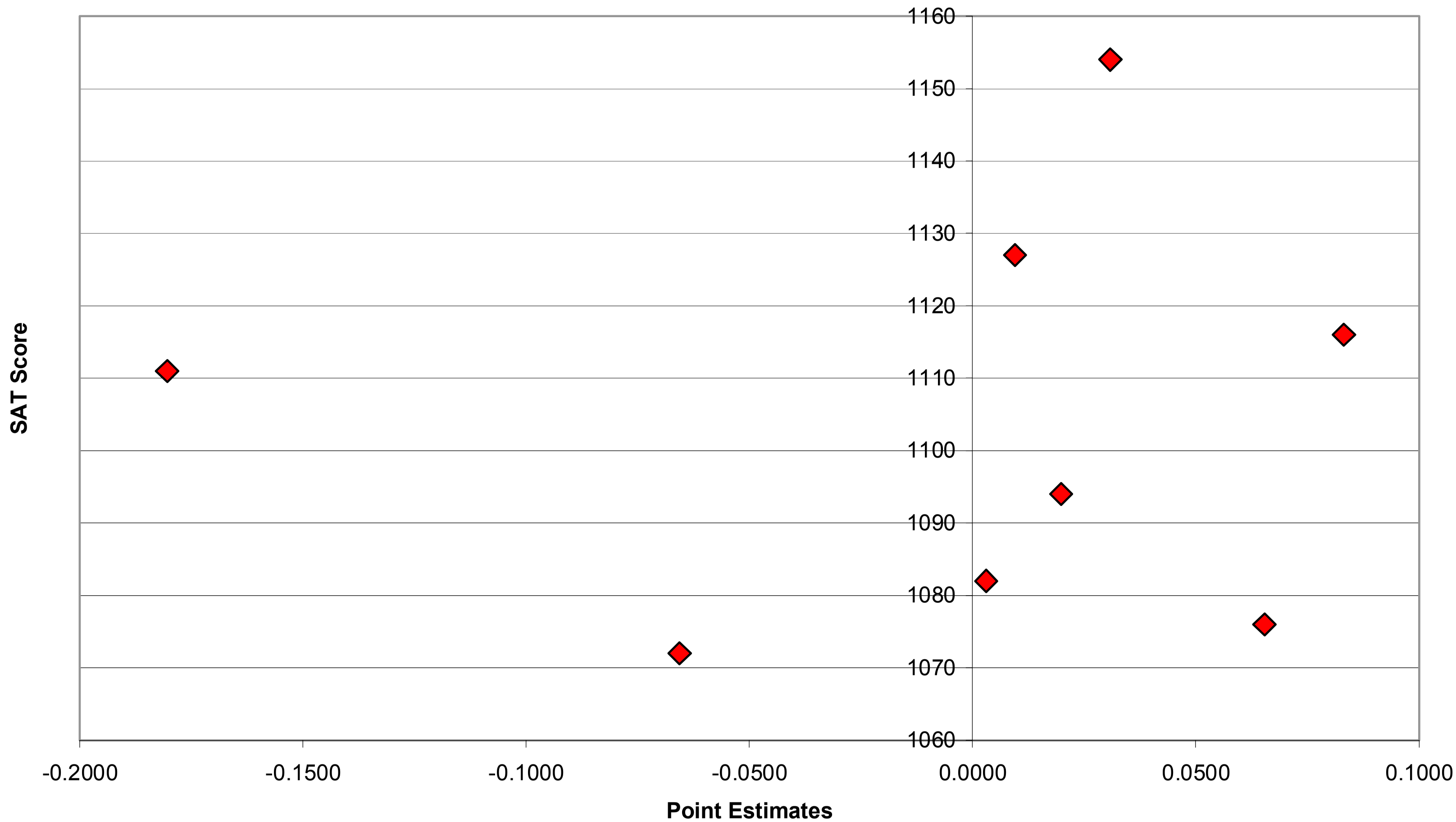

**Figure 4b:**
**1998-1999 Average Math SAT Scores Versus High School Diploma Coefficient Point Estimates**

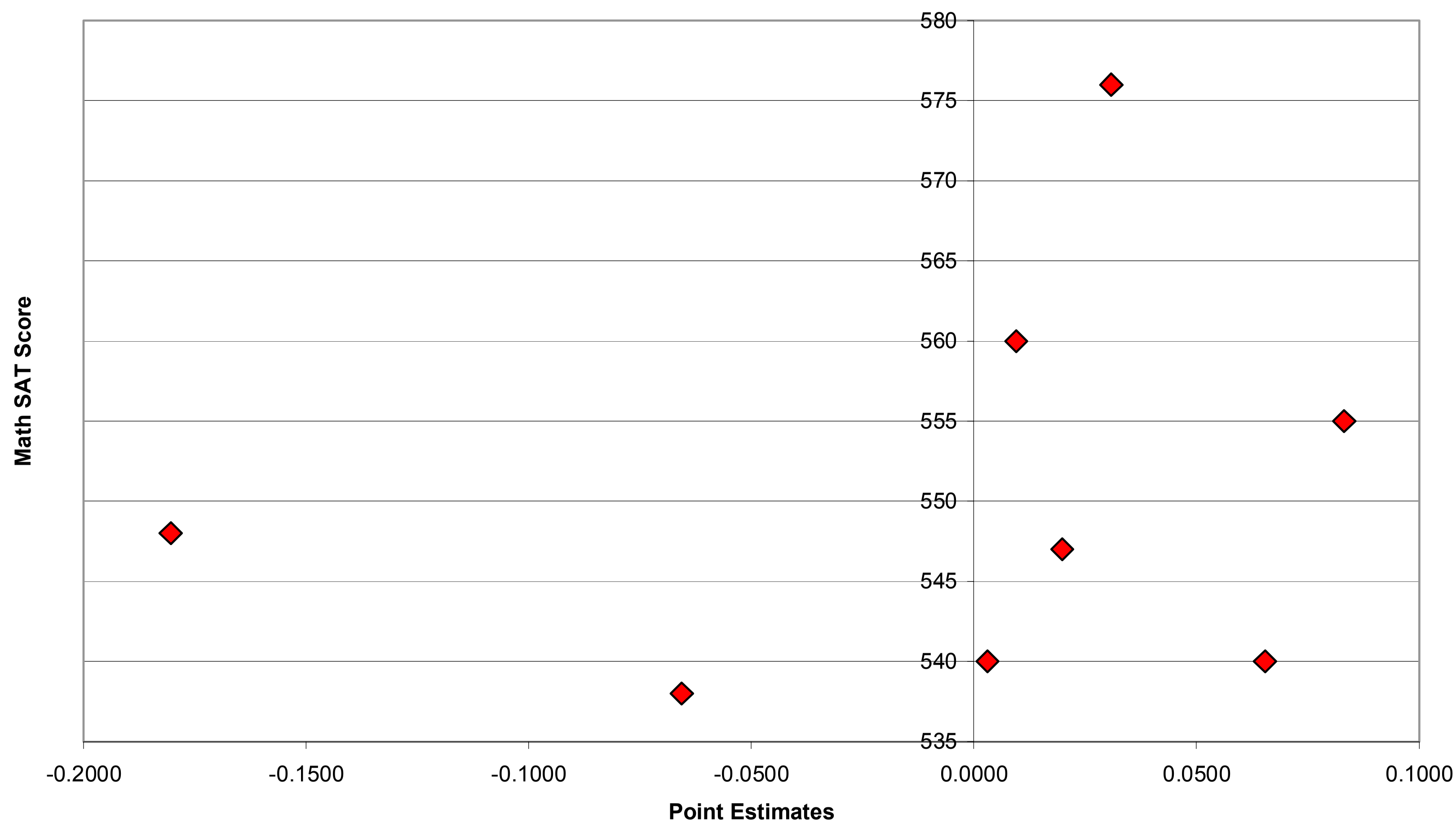

**Figure 4c:**
**1998-1999 Average Verbal SAT Scores Versus High School Diploma Coefficient Point Estimates**

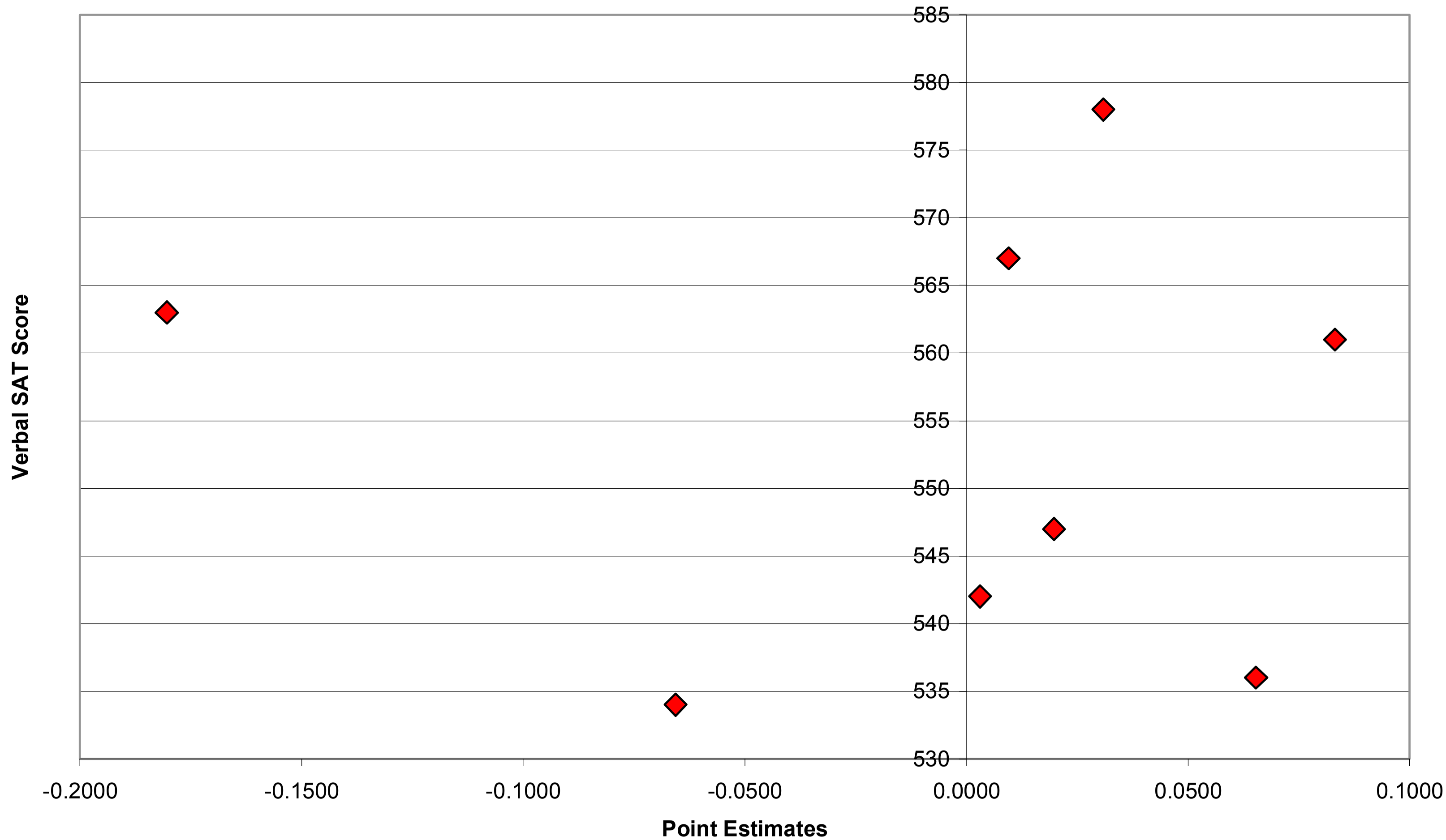

**Figure 5:**
**95% Confidence Intervals and Point Estimates of Within-State Education Regression Coefficents: Some College**

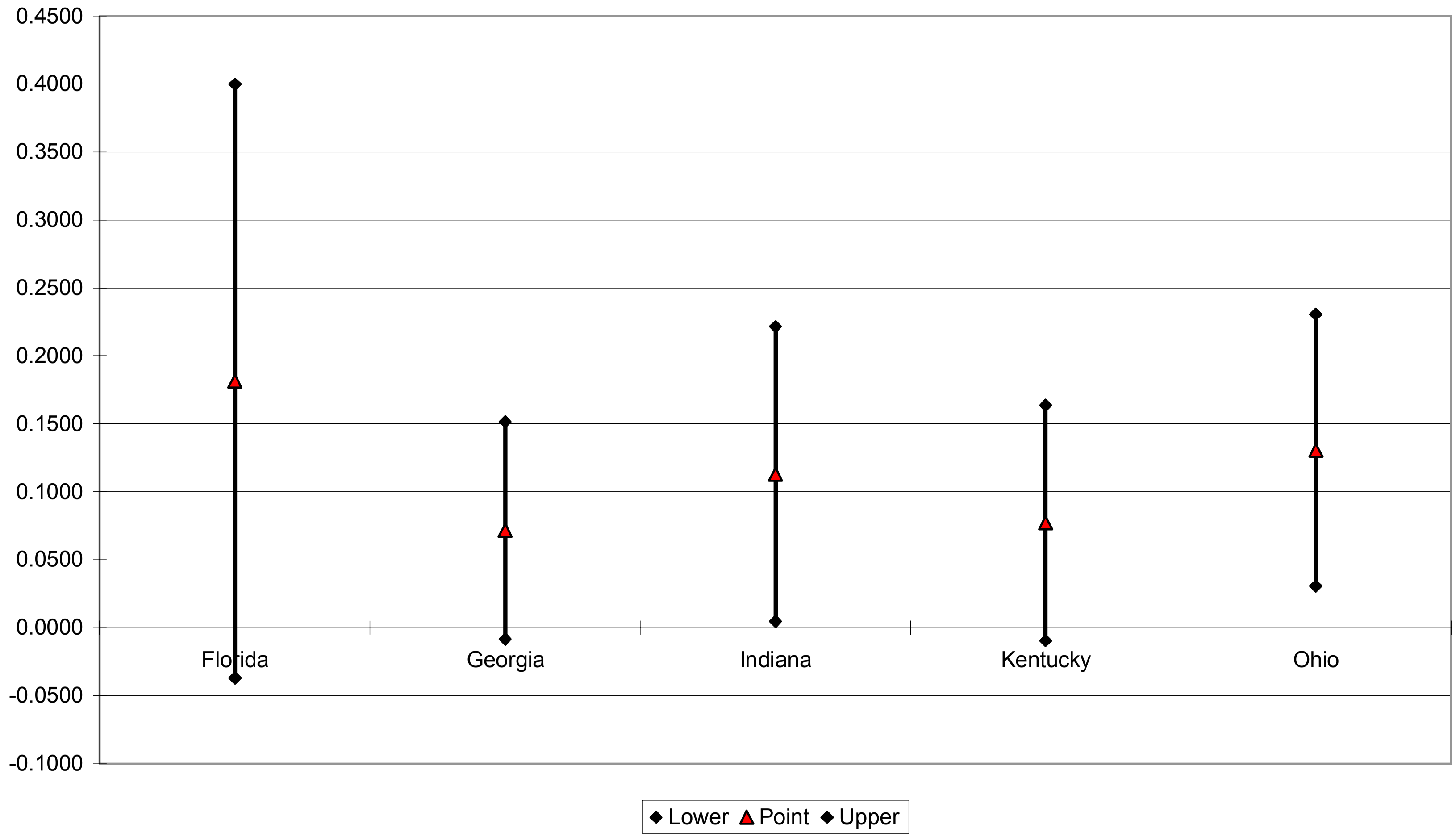

**Figure 6:**
**95% Confidence Intervals and Point Estimates of Within-State Education Regression Coefficents: Bachelor Degree or Higher**