GROWTH AND CONVERGENCE ACROSS THE UNITED STATES: EVIDENCE FROM COUNTY-LEVEL DATA

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Abstract—We use U.S. county data (3,058 observations) and 41 conditioning variables to study growth and convergence. Using ordinary least squares (OLS) and three-stage least squares with instrumental variables (3SLS-IV), we report on the full sample and metro, nonmetro, and and regional samples: (1) OLS yields convergence rates around 2%; 3SLS yields 6%–8%; (2) convergence rates vary (for example, the Southern rate is 2.5 times the Northeastern rate); (3) federal, state, and local government negatively correlates with growth; (4) the relationship between educational attainment and growth is nonlinear; and (5) the finance, insurance, and real estate industry and the entertainment industry correlate positively with growth, whereas education employment correlates negatively.

I. Introduction

WE study growth determination and measure the speed of income convergence within the United States. In so doing, we make four contributions to the empirical economic growth literature.[1] First, we have assembled unusually rich county-level data. In contrast to 100–150 observations (typical for existing cross-country, -state, and -regional data sets) our data contain 3,058 observations. The U.S. county data are collected by a single institution using uniform variable definitions. Also, there is no exchange rate variation between the counties, and the price variation across counties is smaller than across countries. Furthermore, U.S. counties are far more homogeneous than countries.[2]

Second, the large number of cross-sectional observations allows us to study not only the full sample, but also regional groups (Northeast, Great Lakes, West, Plains, and South) and metro and nonmetro groups to control for possible cross-regional heterogeneity. Heterogeneity can exist in convergence parameters and also parameters governing the effect of conditioning variables on the level of the balanced growth path.

Third, we use 41 different conditioning variables to assess the empirical relevance of various determinants of

[1] The seminal studies in this area are Barro and Sala-i-Martin (1991, 1992) and Mankiw et al. (1992). Quah (1996) and Sala-i-Martin (1996) survey some of the literature that followed. For a more recent survey, see Brock and Durlauf (2001).

[2] Many of these virtues are embodied in state-level data used by Barro and Sala-i-Martin (1991) and Evans (1997a). However, state-level data sacrifice the large number of observations that we have.

balanced growth path positions. Previous cross-country studies, taken together, have considered as many as 90 different variables as potential growth determinants (Durlauf & Quah, 1999; Durlauf, 2001). As Brock and Durlauf (2001, p. 7) emphasize, however, there are "at best about 120 countries' data available for analysis in cross-sections [and therefore] it is far from obvious how to formulate firm inferences about any particular explanation of growth." Given our large number of cross-sectional observations, we can use the full set of conditioning variables included in our data and still obtain precise estimates of the coefficients.

Fourth, in estimation we employ a cross-sectional variant of Evans's (1997a, 1997b) three-stage least squares (3SLS) approach, as well as ordinary least squares (OLS). Evans (1997b) shows that for the consistency of OLS estimates the data must satisfy highly implausible conditions. He proposes a 3SLS–instrumental variables (IV) method, which produces consistent estimates.

This paper is organized as follows. In section II we discuss the econometric model. In section III we describe the data. In section IV we present the findings regarding the conditional convergence rates, followed by the findings regarding balanced-growth-path determinants in section V. We conclude in section VI.

II. Econometric Model Specification and Estimation

The neoclassical growth model implies that $\hat{y}(t) = \hat{y}(0)e^{-Bt} + \hat{y}^* (1 - e^{-Bt})$, where $\hat{y}$ is the log of income per effective unit of labor, t is the time period, and B is a nonlinear function of various parameters (population growth rate, preference parameters, and so on). B governs the speed of adjustment to the steady state, and $\hat{y}^*$ denotes the steady state. Thus, the average growth rate of income per unit of labor between dates 0 and T is

$$\frac{1}{T}\left[y(T) - y(0)\right] = z + \frac{1 - e^{-BT}}{T}\left[\hat{y}^* - \hat{y}(0)\right], \qquad (1)$$

where z is the exogenous rate of technological progress and B measures the sensitivity of the average growth rate to the gap between the steady state and the initial value. Because the effective units of labor (L) are assumed to equal Le^{zt}, we have $\hat{y}(0) = y(0)$.

Growth regressions are obtained by fitting to the cross-sectional data the equation

$$g_n = \alpha + \beta y_{n0} + \gamma' x_n + \nu_n, \qquad (2)$$

where g_n is the average growth rate of per capita income for economy n between years 0 and T (that is, $[y(T) - y(0)]/T$),

α is a constant representing z, $\beta = (1 - e^{-BT})/T$, x_n is a vector of variables that control for cross-economy heterogeneity in determinants of the steady state $\hat{y}^*$, γ is a vector of coefficients, and v_n is a zero-mean finite-variance error.

OLS can then be used to infer the values of β and γ in equation (2) by regressing the growth rate on initial values of per capita income and other conditioning variables. However, Evans (1997b) shows that for the consistency of OLS estimates, the data must satisfy highly implausible conditions, and argues that plausible departures from them can produce large biases. Specifically, he shows that unless (i) the dynamic structures of the economies studied have identical AR(1) representations, (ii) every economy affects every other economy symmetrically, and (iii) conditioning variables control for all permanent cross-economy differences, the OLS estimates of the speed of convergence are inconsistent—they are biased downward.[3]

Evans (1997b) proposes a 3SLS-IV approach, which produces consistent estimates. The first and second stages involve using instrumental variables (IVs) to estimate the regression

$$\Delta g_n = \omega + \beta\, \Delta y_{n0} + \eta_n, \tag{3}$$

where $\Delta g_n = [(y_{n,T} - y_{n,0})/T] - [(y_{n,T-1} - y_{n,-1})/T]$, $\Delta y_{n0} = y_{n0} - y_{n,-1}$, ω and β are parameters, and η_n is the error. As instruments we use the lagged values of the variables x_n.[4] Given our sample period, we define $\Delta g_n = [(y_{n,1998} - y_{n,1970})/T] - [(y_{n,1997} - y_{n,1969})/T]$.

We use β^*, the estimate from equation (3), to construct the variable $\pi_n = g_n - \beta^* y_{n0}$, which is regressed on the vector x_n. Thus, the third-stage regression is of the form

$$\pi_n = \tau + \gamma x_n + \varepsilon_n, \tag{4}$$

where τ and γ are parameters and ε_n is the error. OLS yields a consistent estimator γ^*.

Of note, γ is not technically the partial effects of x_n variables on the heights of the balanced growth paths. Those partial effects are functions of β as well as γ. However, if the neoclassical (exogenous) growth hypothesis is true ($\beta < 0$), then the signs of elements of γ will be the same as those of the partial effects of given elements x_n. As well, given the assumption that β is identical across economies, the magnitude of γ elements *relative* to one another expresses the magnitudes of the partial effects *relative* to one another. Thus, though γ^* does not allow for precise quantitative statements about the effects of given conditioning variables on balanced growth paths, it does allow for statements about the signs of such effects, as well as how important those effects are relative to each other.

To summarize, we use a three-stage procedure. In the first and second stages, we difference out any uncontrolled form of heterogeneity to eliminate omitted variable bias.[5] In the third stage, the estimate of β is used to re-create the component of a growth regression that would be related to conditioning variables. This component is regressed on a constant and the conditioning variables, in undifferenced form, to estimate the partial correlations of conditioning variables with the growth rate. This procedure ensures that none of the information contained in the levels of the conditioning variables is lost.[6]

We use a Hausman test to determine the appropriateness of the IV approach. Two tests—the first run on the β^*-values and the second on the entire model—yielded m-values of 134.6 and 1236.6, respectively. Both tests reject the null at the 1% level, suggesting that the OLS estimates are inconsistent, and confirming the importance of using the IV method for addressing the potential endogeneity of conditioning variables.[7]

To allow for a possible spatial correlation between the error terms of the counties located in a proximity with each other, we follow Rappaport and Sachs (2003) in reporting a generalization of the Huber-White heteroskedastic-consistent estimator based on Rappaport's (1999) implementation of Conley's (1999) correction to obtain standard errors that are robust to such a spatial correlation. Rappaport and Sachs specify a cutoff distance $\bar{d}$ and assume that the covariance between the errors of two counties is 0 if the

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[3] These results, due to Evans (1997b), are included in an appendix, available from the authors.

[4] These are the 1969 values of conditioning variables with the exception of metro area, water area, and land area. See the data appendix for details, and table 1 for a list of our conditioning variables.

[5] The derivation of equation (3) assumes constancy of the conditioning variables, allowing them to be differenced out. Nazrul Islam has noted that though this might hold for (say) an index of democracy for an international sample over 15 years, some of the county-level conditioning variables could potentially vary. To make sure that this did not introduce significant omitted variable bias, we ran the three IV regressions for the full U.S., metro U.S., and nonmetro U.S. with differenced values of all conditioning variables included as regressors. All point estimates of β from the modified IV regressions fell within the 95% confidence intervals of the Evans methods IV estimates. As well, if the β estimates are not significantly affected, then neither are the third-stage results.

[6] Following a referee's suggestion, we have estimated the model using a panel generalized method of moments (GMM) method as well. However, the resulting estimates, which we generated using the method of Caselli, Esquivel, and Lefort (1996), did not make much sense. We believe the main reason for the failure of the panel GMM approach is that it may be ill suited for our data because our sample does not form a true panel. Although we have over 3,000 cross-sectional observations, over time we only have three time series observations (the 1970, 1980, and 1990 decennial Census data), and it appears that it is not enough to carry the level information forward after the variables are differenced, which is necessary for implementing panel GMM estimation. 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, so that the most important information is in the levels.

[7] It may be argued that some of the variables we use, such as educational variables, are endogenous, reflecting perhaps institutional and cultural features that lead to demand for various levels of schooling in various counties. Though this might be the case, we believe the problem is unlikely to be severe. This is because in the model we estimate, the right-side variables are temporally prior to the regressor. Also, we use IVs to resolve whatever endogeneity problem might still be there. Finally, we used a Hausman test to check for—and confirmed—the appropriateness of the instrumental variables approach.

FIGURE 1.—METRO AND NONMETRO COUNTIES—CONTINENTAL UNITED STATES
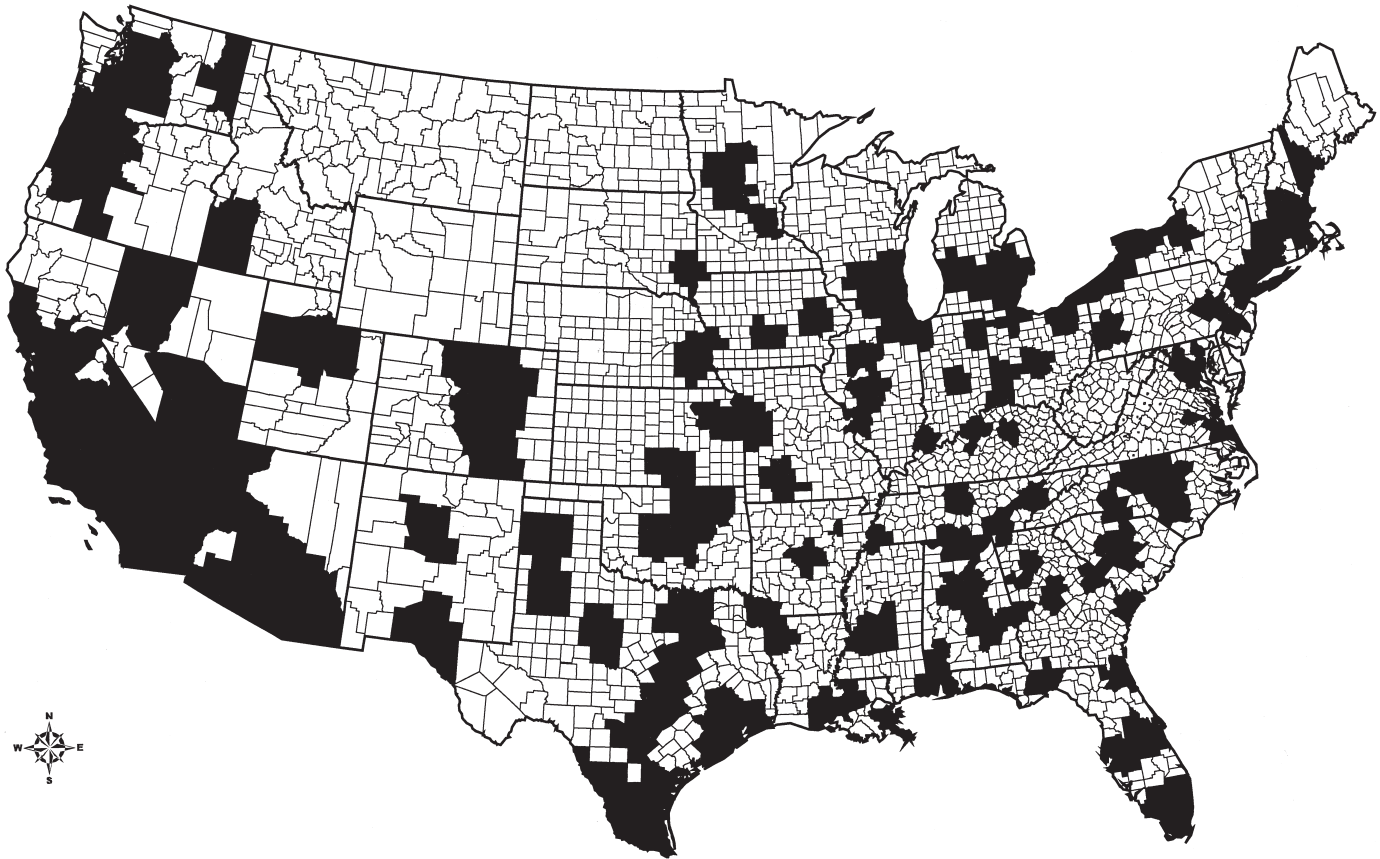
Note:
(1) Alaska has 3 metro counties including and surrounding the city of Anchorage.
(2) Hawaii has 1 metro county that contains Honolulu.
(3) Metro counties are shaded black.

Euclidean distance between the counties centers exceeds $\bar{d}$. Otherwise, they impose declining-weight structure on the covariance by defining a distance function $g(d_{ij}) = 1 - (d_{ij}/200)^2$, where d_{ij} is the distance between the centers of counties i and j, and assuming that $E(\varepsilon_i\varepsilon_j) = g(d_{ij})\rho_{ij}$, where $\hat{\rho}_{ij} = e_ie_j$, and that $g(d_{ij}) = 1$ for $d_{ij} = 0$, $g(d_{ij}) = 0$ for $d_{ij} > \bar{d}$, and $g'(d_{ij}) \leq 0$ for $d_{ij} \leq \bar{d}$. Thus, Rappaport's (1999) implementation of the correction assumes that the covariance between the error terms falls off quadratically as the distance between the counties increases to $\bar{d} = 200$ km. The corrected standard errors are used in calculating the confidence intervals reported under the CR (Conley-Rappaport) column in tables 2 and 3.[8] In sum, we present three sets of estimates: OLS, CR-OLS, and 3SLS.[9]

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[8] We are grateful to Jordan Rappaport for sharing with us his computer codes and for helping us in implementing the CR correction.

[9] The OLS and the CR-OLS point estimates are the same; only the standard errors differ. The actual significance of the CR correction appears to vary across the regions. According to the figures in tables 2 and 3, the CR standard errors are sometimes larger than the OLS standard errors. But often they are the same as, or are even smaller than, the OLS standard errors, which is consistent with Conley's (1999) conclusion that spatial correlation does not necessarily increase the standard errors. We shall note

III. U.S. County-Level Data

The data we use are drawn from several sources, but the majority come from the Bureau of Economic Analysis Regional Economic Information System (BEA-REIS) and U.S. Census data sets. The BEA-REIS data are largely based on the 1970, 1980, and 1990 decennial Census files; the 1972, 1977, 1982, and 1987 Census of Governments; and the Census Bureau's City and County Book from various years. We exclude military personnel from the measurements of both personal income and population.

Our data contain 3,058 county-level observations. The large number of observations allows us to explore possible heterogeneity across the U.S regions by splitting the data into two sets of subsamples. The first set separates the data into 867 metro and 2,191 nonmetro counties (figure 1).[10] The second set separates the data into five regions: Northeast, Great Lakes, West, Plains, and South. Given the large

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that the CR correction was not implemented within the 3SLS framework because the statistical properties of the resulting estimators are not known.

[10] Metro counties are those that contain cities with populations of 100,000 or more, or border such counties.

TABLE 1.—DEFINITIONS AND SOURCES OF VARIABLES

Variable	Definition	Period	Source
Income	Per capita personal income (excluding transfer payments)	1969–1998	BEA
Land area per capita	Land area in km^2/population	1970–1990	Census
Water area per capita	Water area in km^2/population	1970–1990	Census
Age: 5–13 years	Percentage of 5–13-year-olds in the population	1970–1990	Census
Age: 14–17 years	Percentage of 14–17-year-olds in the population	1970–1990	Census
Age: 18–64 years	Percentage of 18–64 year olds in the population	1970–1990	Census
Age: 65+	Percentage of 65 + -year-olds	1970–1990	Census
Black	Percentage of blacks	1970–1990	Census
Hispanic	Percentage of Hispanics	1970–1990	Census
Education: 9–11 years	Percentage of population with 11 years education or less	1970–1990	Census
Education: H.s. diploma	Percentage of population with high school diploma	1970–1990	Census
Education: Some college	Percentage of population with some college education	1970–1990	Census
Education: Bachelor +	Percentage 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
Poverty	Percentage of the population below the poverty line	1970–1990	Census
Federal government employment	Percentage of population employed by the federal government in the county	1969–1998	BEA
State government employment	Percentage of population employed by the state government in the county	1969–1998	BEA
Local government employment	Percentage of population employed by a local government in the county	1969–1998	BEA
Self-employment	Percentage of population self-employed	1970-1990	Census
Agriculture	Percentage of population employed in agriculture	1970–1990	Census
Communications	Percentage of population employed in communications	1970–1990	Census
Construction	Percentage of population employed in construction	1970–1990	Census
Entertainment and recreational services	Percentage of population employed in entertainment and recreational services	1970–1990	Census
Finance, insurance, and real estate	Percentage of population employed in finance, insurance, and real estate	1970–1990	Census
Manufacturing: durables	Percentage of population employed in manufacturing of durables	1970–1990	Census
Manufacturing: nondurables	Percentage of population employed in manufacturing of nondurables	1970–1990	Census
Mining	Percentage of population employed in mining	1970–1990	Census
Retail	Percentage of population employed in retail trade	1970–1990	Census
Transportation	Percentage of the population employed in transportation		
Business and repair services	Percentage of population employed in business and repair services	1970–1990	Census
Educational services	Percentage of population employed in education services	1970–1990	Census
Professional related services	Percentage of population employed in professional services	1970–1990	Census
Health services	Percentage of population employed in health services	1970–1990	Census
Personal services	Percentage of population employed in personal services	1970–1990	Census
Wholesale trade	Percentage of population employed in wholesale trade	1970–1990	Census
College town	Dummy variable: 1 if the county had a college or university enrollment to population ratio greater than or equal to 5%, and 0 otherwise.	1970	National Center for Educational Statistics
Metro area 1970	Dummy variable: 1 if the county was in a metro area in 1970, and 0 otherwise	1970	Census

All BEA variables are available annually from 1969 to 1998. All Census variables are gathered from the 1970, 1980, and 1990 Census tapes. Values for 1969 were obtained via the interpolation method as discussed in section III.

sample, the subsample analysis sacrifices little in degrees of freedom. As an additional control we include state dummies in all regressions.

We use the BEA's measure of personal income, which along with county population gives per capita income. We adjust it to be net of government transfers and express it in 1992 dollars. Natural logs of real per capita income are used throughout. In addition to initial income, we utilize 40 demographic conditioning variables, listed in table 1.[11]

IV.   Analysis of Convergence Rates

Table 2 reports the asymptotic conditional convergence rate estimates along with their 95% confidence intervals for all three estimation methods (OLS, CR-OLS, and 3SLS)

[11] An appendix at the end of the paper describes the data in more detail.

across all different subsamples considered. Following Evans (1997b, p. 16), we use the expression $c = 1 - (1 + T\beta)^{1/T}$ to infer the asymptotic rate of convergence from the estimates of β.[12] The confidence intervals are obtained by

[12] The estimates of β, the coefficient on the log of 1970 real per capita income, are not reported here to save space. Also, the estimates of β when conditioning variables are excluded (which represents the hypothesis of absolute convergence) are much smaller in absolute value [for example, -0.0068 (OLS) compared to -0.0173 (OLS) and -0.0344 (3SLS) for the entire sample] than their conditional counterparts, suggesting that the balanced growth paths vary across counties and therefore the determinants of the balanced growth paths need be conditioned upon. The unconditional β estimates, though smaller, are still negative and significant at the 1% level for the full sample, and for either the metro or the nonmetro samples. Thus, we cannot reject absolute convergence, but only conclude that it is very slow. For example, the point estimate of -0.0068 implies an absolute convergence rate of approximately 0.7%. Thus, counties close half the present gap between themselves and the wealthiest county in just under a century.

TABLE 2.—ASYMPTOTIC CONDITIONAL CONVERGENCE RATES: POINT ESTIMATES WITH 95% CONFIDENCE INTERVALS

Region	Area	Number of Counties	OLS Estimates and 95% C.I.	C-R OLS and 95% C.I.	3 SLS Estimates and 95% C.I.
United States	All counties	3,058	0.0239 (0.0224, 0.0255)	0.0239 (0.0213, 0.0267)	0.0658 (0.0632, 0.0981)
	Metro counties	867	0.0167 (0.0142, 0.0194)	0.0167 (0.0137, 0.0201)	0.0834 (0.0749, 0.0944)
	Nonmetro counties	2,191	0.0273 (0.0253, 0.0293)	0.0273 (0.0244, 0.0304)	0.0716 (0.0620, 0.0844)
Great Lakes	All counties	435	0.0219 (0.0179, 0.0264)	0.0219 (0.0189, 0.0252)	0.0501 (0.0446, 0.0564)
	Metro counties	140	0.0126 (0.0064, 0.0201)	0.0126 (0.0107, 0.0147)	0.0661 (0.0549, 0.0818)
	Nonmetro counties	295	0.0282 (0.0223, 0.0353)	0.0282 (0.0241, 0.0330)	0.0525 (0.0447, 0.0626)
New England	All counties	244	−0.0031 (−0.0068, 0.0008)	−0.0031 (−0.0061, −0.0001)	0.0488 (0.0402, 0.0606)
	Metro counties	90	0.0018 (−0.0056, 0.0113)	0.0018 (−0.0007, 0.0047)	0.0506 (0.0364, 0.0756)
	Nonmetro counties	154	0.0028 (−0.0024, 0.0091)	0.0028 (−0.0002, 0.0062)	0.0491 (0.0404, 0.0602)
Plains	All counties	832	0.0249 (0.0221, 0.0281)	0.0249 (0.0214, 0.0289)	0.0496 (0.0345, 0.0775)
	Metro counties	143	0.0095 (0.0049, 0.0148)	0.0095 (0.0066, 0.0127)	0.0518 (0.0404, 0.0692)
	Nonmetro counties	689	0.0255 (0.0223, 0.0289)	0.0255 (0.0216, 0.0298)	0.0571 (0.0410, 0.0847)
Southern	All counties	1,009	0.0232 (0.0205, 0.0261)	0.0232 (0.0205, 0.0261)	0.1149 (0.0985, 0.1451)
	Metro counties	252	0.0218 (0.0159, 0.0287)	0.0218 (0.0170, 0.0272)	0.0757 (0.0672, 0.0865)
	Nonmetro counties	757	0.0229 (0.0199, 0.0262)	0.0229 (0.0203, 0.0258)	0.1180 (0.0975, 0.1693)
Western	All counties	538	0.0318 (0.0276, 0.0365)	0.0318 (0.0273, 0.0369)	0.0724 (0.0590, 0.0953)
	Metro counties	242	0.0128 (0.0084, 0.0178)	0.0128 (0.0091, 0.0169)	0.1393 (0.1003, 0.1563)
	Nonmetro counties	296	0.0356 (0.0296, 0.0428)	0.0356 (0.0308, 0.0411)	0.0846 (0.0694, 0.1105)

Asymptotic convergence rates and 95% confidence intervals are calculated following Evans (1997a). The asymptotic convergence rate (ρ) is determined by substituting the β from equation (3) into the equation $\rho = 1 - (1 + T\beta)^{1/T}$. The calculation of the 95% confidence interval follows two steps. First, we obtain new endpoints by computing $\beta \pm$ its standard error. Second, these new values are substituted into the above equation. "C-R" abbreviates "Conley-Rappaport" and denotes standard errors obtained using Rappaport's (1999) implementation of Conley's (1999) correction for possible cross-county spatial correlation. See section II for details.

computing the endpoints, $\beta \pm 1.96 \times$ s.e.(β), and plugging them into $c = 1 - (1 + T\beta)^{1/T}$.

According to table 2, the estimated conditional convergence rate using 3SLS is 6.58%, significant at the 1% level. Compare this with 2.40% using OLS, also significant at the 1% level. The difference between the two estimates is over 250%, suggesting that OLS introduces a substantial bias. Therefore, we primarily focus below on the 3SLS estimation results.

Metro and nonmetro counties yield similar results. For the metro counties, 3SLS yields a convergence rate of 8.34%, compared to 1.67% with OLS. The analogous numbers are 7.16% and 2.73% for the nonmetro counties (all significant the at 1% level). The overlap between the (narrow) 3SLS confidence intervals suggests that any difference between the metro and nonmetro counties is small. Thus, a consistent estimate of the rate of convergence across the U.S. counties is in the range of 6% to 8%.[13]

Considering the variation in convergence rates by region, we find that it is lowest in Northeast (4.88%) and Plains (4.96%), followed by 5.01% in Great Lakes. The highest rates are found in the West (7.24%) and South (11.49%).[14]

Comparing the results for regional samples broken down into metro and nonmetro samples, we find the biggest difference in the West, where the convergence rate point estimate of the metro counties is 13.93% in contrast to 8.46% for the nonmetro counties. We find a substantial difference in the South also, but in the opposite direction: 11.80% in the nonmetro versus 7.57% in the metro counties. In the remaining regions, the difference is less remarkable. In the Great Lakes the convergence rates of metro and nonmetro counties are 6.61% and 5.25%, respectively; in the Northeast, 5.06% and 4.91%, respectively; and in the Plains, 5.18% and 5.71%, respectively.

V. Analysis of Balanced Growth Path Determinants

Because we do not reject the conditional convergence hypothesis, the effects of conditioning variables are interpreted as *influences on the height of an individual economy's balanced growth path.*[15] By this interpretation, coefficients indicate the correlation of variables with income growth indirectly via the position of the balanced growth path. Given that position, the average growth rate increases (if the balanced growth path is higher) or decreases (if it is lower) as a result of the deviation of the economy from its individual balanced growth path and the convergence effect.

We now focus on these indirect effects of the conditioning variables on balanced growth paths. The variables we

[13] Panel data estimation methods that difference the variables to remove fixed effects tend to report higher convergence rate estimates. For example, Islam (1995), using international data, reports estimates of 4%–5% (even higher for OECD countries). Barro (1997) shows that, because many conditioning variables remain stable, differencing them tends to emphasize measurement error over the correct information contained in the level, biasing convergence rate estimates upward. This argument, however, does not apply here, for two reasons. First, Evans's (1997b) method produces consistent estimates, whereas OLS without differencing does not. Second, the IV regressions of the 3SLS do not include conditionals—differenced or otherwise—so we do not emphasize measurement error in the regressions.

[14] We find no correlation between regional convergence rates and the average rate of economic growth, suggesting that the "conditional" in

conditional convergence is important; for example, Northeast's balanced growth path may be high enough that it continued to grow faster than poorer regions with higher convergence rates.

[15] If convergence were to be rejected, then the coefficients would be better interpreted as influences on individual economies' balanced growth *rates* (Evans, 1997b).

TABLE 3.—ANALYSIS OF GROWTH: THE EFFECT OF SELECT VARIABLES, ENTIRE U.S.

Variables	OLS	C-R OLS	3SLS
	Educational Attainment		
High school diploma	0.0007 (0.0028)	0.0007 (0.0052)	0.0091 (0.0029)[a]
Some college education	−0.0107 (0.0056)[c]	−0.0107 (0.0089)	−0.0014 (0.0061)
Bachelor degree or higher	0.0424 (0.0058)[a]	0.0424 (0.0108)[a]	0.0701 (0.0061)[a]
	Government Employment		
Federal	−0.0145 (0.0048)[a]	−0.0145 (0.0046)[a]	−0.0226 (0.0051)[a]
State	−0.0041 (0.0037)	−0.0041 (0.0045)	−0.0177 (0.0040)[a]
Local	−0.0211 (0.0048)[a]	−0.0211 (0.0079)[a]	−0.0198 (0.0052)[a]
	Industry Composition		
Finance, insurance, and real estate	0.0632 (0.0117)[a]	0.0632 (0.0233)[a]	0.0731 (0.0125)[a]
Education services	−0.0257 (0.0082)[a]	−0.0257 (0.0060)[a]	−0.0445 (0.0087)[a]
Entertainment and recreational services	0.0272 (0.0154)[c]	0.0272 (0.0230)	0.0335 (0.0166)[b]

Standard errors are reported in parentheses. "C-R" abbreviates "Conley-Rappaport" and denotes standard errors obtained using Rappaport's (1999) implementation of Conley's (1999) correction for possible cross-county spatial correlation. See section II for details.
[a]Significant at the 1% level.
[b]Significant at the 5% level.
[c]Significant at the 10% level.

discuss are grouped into educational variables, government employment variables, and industry variables (see table 1). More detailed results are included in an appendix, which is available upon request.[16]

A. Educational Attainment

Our data include eight variables measuring educational attainment. Here we focus on 3SLS results for three of them: the percentages of the population with (i) a high school diploma, (ii) some college education, and (iii) bachelor's degree or more (see table 3). To save space, only the full 3,058-county results appear in table 3.[17]

The coefficient for the population achieving (but not surpassing) a high school diploma is approximately 0.0091%, significant at the 1% level.[18] The results for the percentage of the population with some college, but not a bachelor's degree, are more surprising. The coefficient is −0.0014, but it is not statistically significant. The sign of the coefficient is positive for metro (0.0009) and nonmetro (0.0032) counties. It is in neither case significant, however. Compare this with the (perhaps less surprising) coefficient for the percentage of the population with at least a bachelor's degree, 0.0701, significant at the 1% level. A possible interpretation of these findings concerns the opportunity cost of education. College education ostensibly involves a benefit, in the form of increased skills, but it also involves a cost in the form of wages forgone. The results might lead one to believe that a college education of four years represents a positive net return, whereas the net return on a two-year degree is questionable.[19]

One reason for the positive estimated effect for a bachelor's degree or more may be that *college towns,* that is, counties where a university or college is a substantial percentage of the population, bias the results. College towns have a disproportional number of advanced-degree-holding individuals and may therefore have higher incomes. However, we attempt to control for this by including a college-town dummy variable. We take any college or university that had total enrollment (at a single campus) of 10,000 or more and calculate the ratio of its enrollment to its county's 1970 population. The county's dummy is assigned a value of 1 if this ratio was at least 0.10, and a value of 0 otherwise.[20]

Comparing the metro and nonmetro counties, we find that the coefficient on the bachelor's-degree-or-more variable for the metro and nonmetro counties is 0.1151 and 0.0554, respectively, both significant at the 1% level. Thus, it

[16] Levine and Renelt (1992) show that cross-country regressions may not be robust to small changes in the conditioning variable set. In particular, a "broad array of fiscal-expenditure variables . . . are not robustly correlated with growth" (p. 943). The 3SLS method theoretically yields consistent estimators regardless of the variables included. Further, after running 3SLS regressions for the full sample with all conditioning variables, we ran the regressions without the conditioning variables that initially had coefficient estimates of less than 0.0000 in absolute value and found that the remaining coefficients remained stable. Thus, the 3SLS method seems to help us avoid Levine and Renelt's criticisms in theory and in practice.

[17] The results from the other samples are available on request.

[18] The coefficient on the percentage of the population with 11 years of education or less is −0.0204, significant at the 1% level. This is not surprising. The greater the percentage of an economy's population without minimal skills—not to mention discipline and socialization—necessary for a high school diploma, the lower the balanced growth path.

[19] Kane and Rouse (1995) and Surette (1997) find that the return to a two-year degree is positive, at approximately 4%–6% and 7%–10%, respectively. Neither of these studies, however, uses county data. In addition, they do not take into account the *social* return, which our estimates presumably do. They look at individuals' costs and benefits, whereas we consider their effect on the balanced growth path. What we might be seeing in our results, therefore, is a questionable social return to an associate degree. This is potentially an important finding for policy-makers. As Kane and Rouse (1995, p. 600n.) note, "20 percent of Federal Pell Grants, 10 percent of Guaranteed Student Loans, and over 20 percent of state expenditures for post-secondary education, go to community colleges." If the social return to college education that does not end with a bachelor's degree is not positive, then the subsidies must be reconsidered or restructured as to encourage a bachelor's degree or more as the final outcome. Alternatively, the some-college coefficient may primarily represent the effect of college dropouts, who ultimately obtain no degree at all.

[20] We checked for robustness to a cutoff value of 0.05 also but found no noticeable change in the results.

appears that that level of attainment in a metro area has a considerably larger effect on a balanced growth path than the same level in a nonmetro area.

B. Size of the Public Sector

Our data include variables capturing the size of the public sector at three levels of government. These are the percentage of a county's population employed by (i) the federal government, (ii) the state government, and (iii) the local government.

The issue of whether or not government fosters or hinders economic growth has been explored widely. See, for example, Aschauer (1989), Barro (1991), Easterly and Rebelo (1993), Evans and Karras (1994), and Folster and Henrekson (2001). These studies, however, use government expenditure variables to capture the size and the scope of government activities. We, in contrast, use the percentages of a county's population employed by the federal, state, and local governments.

These variables offer several advantages. First, they allow us to explore how the relationship between government and growth differs at the three levels of decentralization. For example, a reasonable belief may be that local governments can more closely ascertain and respond to the needs of their constituents. The productivity of government may be expected to decrease as it gets more centralized. We can address such a hypothesis, whereas previous studies could not.

Second, the use of three measures of government activity helps us avoid the problems of interpreting coefficients across geographical units when externalities are present; for example, a state government may operate educational institution (at a cost detectable in a growth regression) only to have many of the students, upon graduation, leave to live and work in other states (creating benefits not detectable in growth regressions). In general one would expect externalities to be less important for state than federal government, and less important to an even greater extent for local than state government. As another example, a negative coefficient on the federal government measure might be questioned because the federal services are spread across the nation; a negative coefficient on a local government measure is immune to such a suspicion.

Third, the variables measuring the percentage of population employed allow for a fundamentally different and complementary way of conceptualizing the extent of government's involvement in the economy. The percentage of a population employed by a government can be interpreted as a stock of government activities producing a flow of services, while government expenditures are the flow of services. Moreover, the percentage of a population employed gives a direct perspective on to what extent government is *involved*, that is, how much of labor force is directed by government, rather than simply how much government spends.[21]

Table 3 summarizes the estimation results for the full sample. We find a negative and statistically significant partial correlation between the percentage of the population employed in the public sector and the rate of growth, regardless of whether one considers federal, state, or local government. Moreover, we find no clear pattern of a less negative partial correlation at increasingly decentralized levels. The coefficients for the federal, state, and local employee percentages of the population variables are -0.0226, -0.0177, and -0.0198, respectively, all significant at the 1% level.

However, the relationship might be nonlinear; for example, government might be good to a certain extent, but then become a negative influence as it expands further. To check this, we ran the 3SLS regressions for the full U.S. sample with both linear and quadratic terms, $\gamma_{fl} F + \gamma_{sl} S + \gamma_{ll} L + \gamma_{fs} F^2 + \gamma_{ss} S)^2 + \gamma_{ls} L^2$, where F, S, and L are the percentages of the population employed by federal, state, and local governments, respectively.

With the quadratic terms, the marginal effect of (for example) the federal government variable on the average growth rate is given by $\partial g/\partial F = \gamma_{fl} + 2\gamma_{fs} F$. Thus, a positive coefficient on the linear term and a negative one on the quadratic term imply that the marginal effect of F on g is positive until a level of F where the second term exceeds the first.

The estimation results with the quadratic terms included do not conform to the above. For federal, state, and local government variables entered linearly, the estimates are negative and significant, as in the original regressions. For the quadratic variables, only the federal government coefficient is significant and positive. Using the estimated figures, significant at the 1% and 5% levels, respectively, we obtain $\partial g/\partial F = -0.0331 + 2(0.0477)F$; setting that equal to 0 implies that marginal additions to F are negatively correlated with g for F-values up until 0.35 (until the government employs over 35% of the population), and then marginal additions are positively correlated with g. The overall partial correlation between F and g would not be positive until F exceeded 0.60 (60% of the population). Such F-values, however, are unreasonable for the United States and make little sense.[22] For realistic values, federal government appears negatively correlated with growth.

C. Industry Composition Effects

We have 16 industry-level variables, measuring the percentage of the population employed in a given industry.[23] Interpreting correlations between these variables and in-

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[21] Of course, these are not mutually exclusive. For example, government *spends* on wages so that part of the labor force is *involved* in government actions. This overlap makes the two types of variables complementary.

[22] Only 9 out of 3,058 counties even have F-values as large as 0.30. Also note that military incomes are excluded from our personal income data.

[23] These industries are agriculture; communications; construction; finance, insurance, and real estate; manufacturing of durables; manufacturing of nondurables; mining; retail; business and repair services; educational services; professional and related services; health services; personal services; entertainment and recreational services; transportation services; and wholesale trade.

come growth is difficult, and we stress that the interpretations below are of a speculative nature. We focus on three industries that appear to have significant effects, and about which we feel our speculations are plausible. (See table 3.)

Finance, Insurance, and Real Estate Services: We find a positive correlation between the percentage of the population employed in finance, insurance, and real estate services and economic growth across U.S. counties. The coefficient estimate for the entire sample is 0.0731, significant at the 1% level. The correlation is similar whether one considers the metro (0.0600) or nonmetro (0.0699) subsample (not displayed in table 3), both significant at the 1% level. A possible reason for this finding is the link between financial intermediation and economic growth, as reported by Rousseau and Wachtel (1998), who document quantitatively important links between financial intensity and per capita output level in five OECD countries.[24]

Educational Services: Unlike educational attainment, the percentage of population providing educational services has a negative effect on growth, -0.0445, significant at 1% level. The coefficient is negative also for both metro counties (with the estimate of -0.0577, significant at the 1% level) and nonmetro counties (with the estimate of -0.0335, significant at the 5% level); these results are not displayed in table 3.

One explanation for this correlation is that the benefits of education are not entirely internalized by the providing county.[25] For example, many college graduates do not remain within the county where their colleges are located. The finding discussed above—that educational attainment is positively correlated with growth—is silent as to where a county's population accumulated that stock. Tamura (1991, p. 523) argues that labor moves "... to areas where the external effect is operative." Individuals may attend a college in counties where human capital is easier to acquire, and then move to other counties. This would be particularly true for metro counties where the majority of colleges and universities are located. Indeed, we find that the negative relationship between the percentage of population employed in educational services and economic growth is stronger for the metro counties, in the aggregated data as well as for each region of the United States.[26]

Entertainment and Recreational Services: The effect of this variable on economic growth is positive (0.0335, significant at the 5% level) and is larger in metro counties, with estimates of 0.0670 (significant at the 10% level) and 0.0229 (not significant), for metro and nonmetro counties, respectively. This is potentially important. To put it in perspective, it is larger (in absolute value) than the effect of the public-sector size variables. Also, Costa (1997) reports that, as a percentage of households' budgets, recreation expenses rose from 1.9% in 1890 to 4.5% in 1950 and then to 5.6% in 1991. Entertainment and recreation services, thus, comprise an increasingly large segment of the U.S. economy. The above finding might be capturing the increase in economic activity that is fostered by the presence of gambling casinos and professional sports teams and their stadiums.[27]

VI.   Conclusion and Caveats

We use county-level data from 3,058 U.S. counties to study economic growth and measure the speed of convergence. County-level data are valuable for studying convergence because they form a sample with substantial homogeneity and mobility of resources and technology without sacrificing the benefits of a large number of cross-sectional units. We use 41 different conditioning variables to capture cross-county heterogeneity and to assess how the variables affect the balanced growth paths. We report OLS and 3SLS-IV estimates for the entire data set as well as for its subsets, which include metro and nonmetro counties, and counties grouped into five regions.

We find that whereas OLS yields estimates of the asymptotic convergence rate just above 2%, the 3SLS method consistently estimates a convergence rate between 6% and 8%. This difference is economically significant: it represents a difference in the half-life of the

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[24] Our findings may be interpreted also as offering empirical support to the models of Greenwood and Jovanovic (1990) and King and Levine (1993), in which financial development promotes economic growth. A broad survey of both theoretical and empirical analysis of the link between finance and growth is provided by Levine (2004).

[25] Another explanation for this finding is a possible bureaucratic over-expansion of the public school systems, as suggested by Marlow (2001) and frequently mentioned in media discussions.

[26] Again, the metro, nonmetro, and regional results are available upon request. One may argue that, even in the absence of externalities, we would expect the partial effect of educational services provision to be negative because educational attainment is already controlled for. In other words, employment in provision is the cost, and attainment is the benefit.

Two responses to this argument are possible. First, attainment variables are initial stocks, and so the educational provision variable is also an initial stock. The *flows* from those stocks, which we would expect to contribute to growth over time, are services from human capital and new human capital creation, respectively. Of course, these two flows are likely correlated. Second, we may not expect a negative coefficient on educational provision, because it may proxy, as a measure of input intensity, for educational quality that is not captured in simple attainment stocks. However, it is well known that variation in conventional measures of resources devoted to education (for example, per-student spending, teacher-to-student ratios, and teacher experience or education) generally does a poor job of accounting for variation in student achievement; see, for example, Hanushek (1996). Our negative coefficient estimate is not inconsistent with this regularity.

[27] Siegfried and Zimbalist (2000) reported that by 2005 there would be 95 professional sports stadiums having been constructed since 1990, with more than $27.1 billion spent on them. Eadington (1999) noted that gross gaming revenues had reached $540 billion in 1997. Anderson, Arthur and Co. (1997) and Walker and Jackson (1998) also show that introduction of casino industries can stimulate economic growth.

gap between present levels of income and the balanced growth path of 32–33 years versus 12–13 years, respectively. We also find that the convergence rates are quite variable: the Southern counties converge more than two and half times faster than the counties in the Northeast. In addition, we find that the size of the public sector at *all* levels (federal, state and local) is negatively correlated with economic growth. Further, the relationship between educational attainment and economic growth is nonlinear: it is positive for up to high school, insignificant or even negative for levels between high school and the associate's degree, and then positive for further years of schooling. Finally, a large presence of the finance, insurance, and real estate industry and the entertainment industry is positively correlated with economic growth, while the percentage of a county's population employed in the education industry is negatively correlated with economic growth.

We should stress that the coefficients estimated on our conditioning variables are, strictly speaking, only partial correlations between those variables and a county growth rates. Given the validity of the neoclassical model as a useful approximation to reality, they can be interpreted as the effects of the conditioning variables on balanced growth path positions. However, they are at least interesting as a summary of associations between U.S. county growth rates and a broad set of county demographic measures.

An interesting question that was brought up by one of the referees is that of the applicability of the neoclassical growth model framework to such open economies as the U.S. counties. We agree that the neoclassical growth model may not be the most suitable framework for thinking about growth in a cross section of U.S. counties, given their extraordinary degree of openness.

A way around this problem has been proposed recently by Rappaport (1999, 2005), who offers a version of the neoclassical growth model for studying "local growth," where by local is meant small open economic units constituting a larger entity, such as counties constituting the United States. The distinguishing characteristic of small open economies such as U.S. counties is the extraordinary mobility of labor. The question, then, is how labor mobility affects convergence. Rappaport (1999, 2005) expands the standard neoclassical growth model to allow for labor mobility and demonstrates that the model predicts conditional convergence. Indeed, that is what we find here.[28]

We note also that all convergence rate estimates above are based, ultimately, on a specification from the neoclassical growth model. That model is of a closed economy, and convergence is a phenomenon based entirely on diminishing returns to accumulated capital—specifically, capital accumulated *from the economy's own savings.*[29] However, across U.S. counties, especially within a given state, there is considerable capital mobility. Perfect capital mobility would predict immediate equalization of returns and instantaneous convergence, but[30] convergence rates less than 100% may still obtain for open economies in the presence of adjustment costs as well as imperfect capital markets (Levy, 2000, 2004). Barro, Mankiw, and Sala-i-Martin (1995) demonstrate that gradual convergence will occur if "capital is only partially mobile" because "borrowing is possible to finance accumulation of physical capital, but not accumulation of human capital" (p. 104). If human capital accounts for a significant share of income [for example, Barro and Sala-i-Martin (1992) and Mankiw et al. (1992) suggest approximately 1/2], then this would account for gradual convergence.[31] As well, Barro and Sala-i-Martin (1997) present a model where technological diffusion occurs across economies through imitation of the leader's technologies (which is cheaper than innovation). With increasing costs to imitation (for example, because easier ideas to copy are copied first), gradual convergence will occur. Any of the above assumptions can imply (gradual) conditional convergence and place reality somewhere between the convergence rate of a closed economy and the instant convergence of an open economy with perfect capital markets.

Future research could explore interactions of initial income and schooling variables. For example, schooling may affect the ability of an economy to converge. Similar hypotheses could be made concerning government variables. Another avenue for future research could also consider the possibility of a structural relationship between government expenditures and growth, as suggested by Slemrod (1995).

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[28] Further, Rappaport (1999, 2005) finds that that convergence can be either accelerated (by a positive effect of out-migration on wages) or slowed (by a resultant disincentive for capital accumulation), depending on relative changes in marginal products. Rappaport's (2005) analysis suggests that at low levels of income the latter effect dominates.

[29] This can include both physical and, in the case of the so-called augmented Solow model (for example, Mankiw et al. 1992), human capital.

[30] Because we are looking at *per capita* income convergence, we need not address issues relating to labor mobility in the same way as capital mobility.

[31] At the U.S. state level, there is evidence that even financing of physical capital from one state to another is not perfect. Driscoll (2004) found that state-specific variation in deposits has a large and statistically significant effect on state-specific loans. The intuition is that some firms that do not regard bank loans and forms of direct finance as perfect substitutes, and out-of-state bank lending is not prevalent. U.S. federal regulation, until recently, restricted out-of-state bank lending, and even as late as 1994, more than 70% of bank assets were in the control of within-state entities (Berger, Kashyap, & Hannan, 1995).

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DATA APPENDIX

1. Construction of Metro and Nonmetro County-Level Data

A population size of 100,000 was chosen as the minimum threshold for metro counties, for three reasons.[32] First, the data available were limited with respect to reporting smaller city sizes. Second, the BEA uses 100,000 as the minimum necessary population for classifying a locality as a county for the purpose of processing the county (or county-equivalent) source data.[33] Third, it was felt that cities with smaller populations would not provide the spillover into the surrounding counties needed to justify the decision rule. Note that these populations are of the actual cities, and they do not include the populations in the surrounding metropolitan areas. For example, the population for the city of Atlanta is only the population within city limits and not Fulton County—the county where Atlanta resides. Additionally, this decision rule extends beyond state boundaries. For example, Cincinnati is located in southwestern Ohio. The Cincinnati metro area, however, extends well beyond southwestern Ohio into northern Kentucky and southeastern Indiana. Therefore, when the metro counties are viewed on aggregate it is without regard to state boundaries.

This decision rule also errs on the side of conservatism. It may be the case that metropolitan areas with very large populations expand out beyond what our classification would indicate. However, the majority of the overall population for those metropolitan areas has been captured. Additionally, by erring on the side of conservatism we can be more confident that the metro counties are more homogeneous than they might otherwise be. For example,

[32] In order to determine which cities had populations over 100,000, we used Census Bureau publication SU-99-1, "Population Estimates for Cities with Populations of 100,000 and Greater."

[33] See "Local Area Personal Income, 1969–1992," Bureau of Economic Analysis, Regional Accounts Data, February 2, 2001, p. 1.

because we are unable to further subdivide counties, the farthest reaches of a metropolitan area may contain a county where only a small portion of the population would be classified as belonging to that metropolitan area. If we were to include that entire county as a metro county, we would be incorrectly classifying the entire county.

Our decision to err on the side of conservatism might affect our final results in the following way. The metro county analysis results will be slightly understated because it may be excluding small populations on the outskirts of metropolitan areas, and our nonmetro county analysis results may be slightly overstated for the exact opposite reason—it will be including a population that should be categorized as metro.

That is why we chose not to use the metropolitan statistical areas (MSAs) as defined by the Office of Management and Budget (OMB). An example will help demonstrate the difference. The MSA for Atlanta, GA, as defined by the OMB consists of the following 20 counties: Barrow, Bartow, Carroll, Cherokee, Clayton, Cobb, Coweta, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Newton, Paulding, Pickens, Rockdale, Spalding, and Walton.[34] Our metro classification for Atlanta consists of the following 10 counties: Carroll, Cherokee, Clayton, Cobb, Coweta, DeKalb, Fayette, Forsyth, Fulton, and Gwinnett. The 10 counties included in our metro region contain the largest portion of the metropolitan area, in terms of population. It should be noted that our metro classification contains most of the same MSAs as the OMB's classification. The counties that constitute those regions, however, are different, as demonstrated above. As previously noted, our classification tends to have fewer counties attached to a particular metropolitan area—providing, we believe, a more homogeneous population.

2. Construction of the Regional County-Level Data

To perform the second set of subsample analysis, we have separated the sample into five regional subgroups: Northeast, Great Lakes, Western, Plains, and Southeastern states. The limiting constraint on further increasing the regions was the number of counties within some of the states. For example, a few of the states in the Northeast Region have less than ten counties. Given the number of independent variables, it was necessary to increase the size of the regions in order to increase the overall number of observations. An attempt was made to group states that were closely related to each other as much as possible in their economic and socioeconomic characteristics.[35]

Given the data constraints, it was necessary to use an interpolation procedure for some variables.[36] In this study we cover the 1970–1998 period. However, in order to implement the Evans's (1997a, 1997b) 3SLS estimation method as described in section II, we needed to have available data values for 1969 and 1997. We used linear interpolation to generate these missing observations. It should be noted that none of the data relating to income and population variables were generated by this method, as they were available from BEA-REIS on a yearly basis for the entire period covered. The Census data variables, which were available in 1970, 1980, and 1990, were interpolated in order to generate the 1969, 1997, and 1998 values.

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[34] The city of Atlanta is located in Fulton County.

[35] The regional breakdown of the individual states is as follows (the figures in parentheses indicate the number of counties in the given state). *Northeast:* Maine (16), New Hampshire (10), Vermont (14), Massachusetts (14), Connecticut (8), Rhode Island (5), Delaware (3), Washington, DC (1), Maryland (24), New Jersey (20), New York (62), and Pennsylvania (67); *Great Lakes:* Illinois (102), Indiana (92), Michigan (83), Ohio (88), and Wisconsin (70); *West:* Alaska (9), California (58), Hawaii (4), Nevada (17), Oregon (36), Washington (39), Arizona (9), New Mexico (32), Oklahoma (77), and Texas (254); *Plains:* Iowa (99), Kansas (106), Minnesota (87), Missouri (113), Nebraska (93), North Dakota (53), South Dakota (66), Colorado (63), Idaho (44), Montana (56), Utah (29), and Wyoming (23); and *South:* North Carolina (100), South Carolina (45), Georgia (159), Florida (67), Tennessee (95), Alabama (67), Mississippi (82), Louisiana (64), Arkansas (74), Kentucky (120), Virginia (84), and West Virginia (55). This yields a total of 3,058 counties. (The original sample contained 3,066 counties, but 8 counties were excluded for lack of data.)

[36] Given the cross-sectional nature of our data, the use of interpolation does not cause problems of the type reported by Dezhbakhsh and Levy (1994), who focus on the periodic properties of interpolated time series.

3. 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) the Census Bureau database, and (2) the 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. This money income information is based on the values self-reported 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, that is, the years in which the decennial Census survey is conducted.

The second source for these data, and the one chosen for this project, is personal income as measured by the Bureau of Economic Analysis (BEA).[37] 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 pretax 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 nonfarm. Per capita income is defined as the ratio of this personal income measure to the population of an area.[38]

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 intercounty 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 multicounty metropolitan area and in many nonmetropolitan 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.

Obviously, metro areas and the surrounding counties will have a higher proportion of cross-county commuters. By using our classification system for metro counties we alleviate any problems that might arise with the BEA's adjustment process, as we are grouping the metro counties into one single observation unit. Moreover, the classification we have in place should pick up the majority of cross-county commuters.

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[37] 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.

[38] 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 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 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. 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.