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Abstract: We use new US county level data (3,058 observations) from 1970 to 1998 to explore the relationship between economic growth and the size of government at three levels: federal, state and local. Using 3SLS-IV estimation we find that the size of federal, state and local government all either negatively correlate with or are uncorrelated with economic growth. We find no evidence that government is more efficient at more or less decentralized levels. Furthermore, while we cannot separate out the productive and redistributive services of government, we document that the county-level income distribution became slightly wider from 1970 to 1998. Our findings suggest that a release of government-employed labor inputs to the private sector would be growth-enhancing.

JEL Codes: O40, O11, O18, O51, R11, H50, and H70

Key Words: Economic Growth, Federal Government, State Government, Local Government, and County-Level Data

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I. Introduction

We study the role of various levels of government (federal, state and local) in US growth determination from 1970 to 1998. Our analysis is based on the exceptionally rich county-level dataset that has been assembled recently by Higgins, et al. (2006), Young, et al. (2006a) and Young, et al. (2006b) to study conditional convergence in the US. In contrast to the 100 to 150 observations typical in the extant literature, the data contain over 3,000 county-level observations. To measure the extent of the government's involvement in the economy, we use the percentage of the population employed by the federal, state, and local governments in each county.

These variables complement those typically used in the literature. For example, taxes, government expenditures, and government capital stocks have been used as proxies for the extent of the public sector (Atkinson, 1995; Slemrod, 1995; Agel, et al., 1997; and, Rodrik, 2005). We, in contrast, use a direct measure of the percent of a county's labor force that is under the direction of some level of government. Furthermore, whereas some studies (e.g., Sala-i-Martin 1997a and 1997b) are able to break down government expenditures into investment, consumption and education, we analyze the effects of the public sector at the federal, state and local levels separately. As far as we know, no studies have used government employment data at varying degrees of decentralization for studying economic growth.

Moreover, the large number of cross-sectional observations allows us to study the US as a whole as well three sets of sub-samples of interest: (i) metro and non-metro counties, (ii) five US regions (Great Lakes, Northeast, Plains, Southern, and Western states), and (iii) 32 individual states. Metro and non-metro sub-samples allow for the possibility that government's effect on economic growth varies with population density. For instance, a higher population density may lead to negative externalities that the public sector is uniquely suited to deal with. Furthermore, regional and individual state samples allow for the possibility of heterogeneity of institutions and cultures conducive to relatively good or bad government (in terms of growth-determination). For example, the general view of what activities government should pursue may be radically different in various sections of the country. This carries over to the federal level if individual states request, allow, and/or encourage different types of federal activities; then the effects of government on economic growth may be significantly different.

In addition to the three measures of government employment variables, our analysis incorporates 38 other variables (as well as state-dummies for the nation-wide samples) to condition the growth rates of per capita income on. Given the large number of cross-sectional observations, our analysis represents a unique response to the criticisms of Levine and Renelt (1992), Sala-i-Martin (1997a and 1997b) and Sala-i-Martin, et al. (2004). These authors note that finding statistically significant effects for measures of the public sector is not robust as it is very sensitive to the inclusion of other conditioning variables.[1] Motivated by the "extreme bounds" analysis of Leamer (1983), they devise methods to determine robustness in the face of a large number of conditioning variables when degrees of freedom only allow a small number of conditioning variables in a given regression. With over 3,000 county-level observations, we can include a large number of

[1] Levine and Renelt (1992) incorporate over 50 conditioning variables while Sala-i-Martin (1997a and 1997b) and Sala-i-Martin, et al. (2004) incorporate over 60. Studies of economic growth at the country-level have, taken together, considered as many as 90 different variables as potential growth determinants (Durlauf and 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." Such an observation holds for studies using US state-level data as well.

conditioning variables while maintaining ample degrees of freedom.

In terms of econometric methodology, we follow Higgins, et al. (2006) and employ a cross-sectional variant of a 3SLS-IV approach first developed by Evans (1997b) for estimating the growth equations. Evans (1997b) and Caselli, et al. (1996) show that data must satisfy highly implausible conditions for OLS estimators to be consistent. The 3SLS-IV estimation differences uncontrolled heterogeneity out of income growth rates and then consistently estimates the effect of initial income levels; that estimated effect is then used to recover the effect of government variables in the third-stage estimation.[2]

To briefly summarize the main results, we find that the size of the US government at all three levels of decentralization (federal, state, and local) is either uncorrelated with or is negatively correlated with US county-level economic growth. Moreover, we find no evidence of government activities becoming more productive at more (or less) decentralized levels. Although we find that the county-level income distribution became marginally wider from 1970 to 1998, it does not appear that the lack of productive contribution of the public sector was compensated for by changes in the nature or the scope of its redistributive effects. We conclude that government activities at all three levels of decentralization are unproductive in the long run as they are growth-hindering.

The remainder of the paper is organized as follows: section II discusses the relation of this paper to recent literature on US growth determination; section III discusses our econometric methodology and data; section IV presents and discusses our

[2] Caselli, et al. (1996) suggests a panel GMM method that differences out omitted variable bias and uses instruments to alleviate endogeneity concerns. This method, however, is useful if there is enough time sectional dimension and, therefore, a cross-sectional estimation technique appears more appropriate. See footnote 9 below.

empirical findings; and section V concludes.

II. Government and growth in the US

We focus on the percentage of a county's population employed by (i) the federal government, (ii) the state government, and (iii) the local government. From a long-run perspective these can be viewed as either the stock of labor force under the allocative command of the public sector, or they can be considered as the (annual) flow of labor services into the production of government services.

The extant literature focusing on US data uses state-level government capital and/or expenditure variables in a production function framework. Recent examples include Evans and Karras (1994) who use disaggregated government capital and expenditure measures. They conclude that only current government expenditures on education are productive and government capital, as an input, has a negative effect on productivity. Holtz-Eakin (1994, p. 13) also finds "…essentially no role for public-sector capital at the margin." Garcia-Milàl, et al. (1996) echo this finding.

Shioji (2001) criticizes the production function approach and instead derives a version of an income convergence equation (Barro and Sala-i-Martin, 1992 and Mankiw, et al., 1992). Shioji finds that the infrastructure component of government capital has a positive effect on economic growth.

The variables we use complement the aforementioned studies and offer several advantages. First, they allow us to explore how the relationship between government and growth differs at three levels of decentralization. Second, they are helpful when externalities are present across geographical units. For example, a state government may operate educational institutions (at a cost detectable in a growth regression) only to have many of the students graduate and leave to live and work elsewhere (creating benefits not detectable in growth regressions). As another example, a negative coefficient on the federal government measure might be questioned because federal services are spread across the nation. In general, one would expect externalities across counties to be less important for analyzing state than federal government, and even less important for analyzing local than state government. We can at least separate out the local government contribution.

Finally, the percentage of a population employed by some level of government gives a direct perspective on government *involvement*, i.e., how much of the labor force is directed by government, rather than simply how much it spends or how many structures it has built. Of course, these are not mutually exclusive. For example, government *spends* money on wages so that part of the labor force is *involved* in government activities. Also, when government makes expenditures, in general, it competes with the private sector demand and, in part, determines the allocation of private sector resources, including labor. This overlap makes expenditure and employment variables complementary.

III. Empirical specification and data

A. The model and 3SLS-IV estimation procedure

The basic specification used in growth regressions arises from the neoclassical growth model.[3] The growth model implies that,

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

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

where $\hat{y}$ is the log of income per effective unit of labor, t denotes the time, and B is a nonlinear function of various parameters (preference parameters, population growth rate, etc). B governs the speed of adjustment to the steady state, $\hat{y}^*$. From (1) it follows that the average growth rate of income per unit of labor between dates 0 and T is,

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

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 income and the initial value. Since 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,

(3) $$g_n = \alpha + \beta y_{n0} + \gamma' x_n + v_n .$$

In (3), g_n is the average growth rate of per capita income for economy n between years 0 and T [i.e., $\frac{1}{T}\left(y(T) - y(0)\right)$], the constant α is a function of z, $\beta = \left(\frac{1-e^{-BT}}{T}\right)$, x_n is a vector of variables that control for cross-economy heterogeneity in determinants of the steady-state, γ is a coefficients' vector, and v_n is a zero mean, finite variance error term.

Caselli, et al. (1996) and Evans (1997b) show that OLS will be consistent only if the data satisfy highly implausible conditions. According to Evans (1997b), unless (i) the economies have identical AR(1) representations, (ii) every economy affects every other economy symmetrically, (iii) the conditioning variables control for all permanent cross-economy differences, and (iv) the right hand side variables are exogenous, the OLS estimates of β are inconsistent—they are biased downwards.[4]

Evans (1997b) proposes a 3SLS-IV method that produces consistent estimates. In the first two stages, instrumental variables are used to estimate the regression equation,

$$(4) \qquad \Delta g_n = \omega + \beta \Delta y_{n0} + \eta_n ,$$

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 log of per capita income for county *n*, ω and β are parameters, and η_n is the error.[5,6] We use the lagged (1969) values of all x_n variables except *Metro*, *Per-Capita Water Area*, and *Per-Capita Land Area* as instruments.[7] Given our sample period, we define

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

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[4] These results, derived by Evans (1997b), are included in the referee appendix.

[5] An immediate concern with the use of (4) is the reliance on the information from the single difference in the level of income (1969 to 1970) to explain the difference in average growth rates over overlapping time periods (1969 to 1997 and 1970 to 1998). Given that the growth determination is a stochastic process, the potential problem is basically one of a high noise to signal ratio. We are relying on large degrees of freedom to alleviate this problem and identify coefficients. Indeed, we obtain statistically significant β estimates for the full sample as well as for 32 individual states.

[6] As Evans (1997b) shows, the derivation of this equation depends on the assumption that the x_n variables are constant during the time frame considered, allowing them to be differenced out. Since the difference is only over a single year and these are variables representing broad demographic trends, this does not seem to be unwarranted. To make sure that this did not introduce significant omitted variable bias into our estimations, we ran the IV regression for the full US sample with differenced values of all conditioning variables included as regressors. The point estimate of β from the modified IV fell within the 95 percent confidence interval of the Evans method IV estimate. If β estimates are not significantly affected then neither are the third stage results (see below).

[7] See the data appendix for details and Table 1 for the list of the conditioning variables.

Next, we use β^*, the estimate from (4), to construct the variable

$$\pi_n = g_n - \beta^* y_{n0}. \tag{5}$$

In the third stage, we use the OLS to regress π_n on the vector x_n, which consists of the potential determinants of the balanced growth path levels. That is,

$$\pi_n = \tau + \gamma x_n + \varepsilon_n, \tag{6}$$

where τ and γ are parameters and ε_n is the error term. This regression yields a consistent estimator, γ^*.[8] Also note that in principle τ is the same as the OLS α: it is an estimate of the exogenous rate of technical progress, z, or the balanced growth *rate*.

Thus, to briefly summarize the 3SLS-IV procedure we use, in the first two stages, it differences out any uncontrolled form of heterogeneity to eliminate omitted variable bias and then, in the third stage, it uses the resulting estimate of β to recreate the component of the standard growth regression that would be related to conditioning variables. This component is 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 is ideal for data with a large number of cross-sectional

[8] Technically speaking, γ is not the partial effects of x_n variables on the heights of the balanced growth paths. Those partial effects are functions of β and γ. However, if the neoclassical growth hypothesis is true ($\beta < 0$), then signs of elements of γ will be the same as those of the partial effects of given x_n elements. Assuming that β is identical across economies, the size of γ elements relative to one another expresses the magnitude of the partial effects relative to one another. Thus, while γ^* does not allow for precise quantitative statements about the effects of given variables on balanced growth paths, it does allow for statements about the sign of such effects, and how important those effects are relative to each other.

observations and it also ensures that no information contained in the levels of the conditioning variables is lost.[9]

Along with the 3SLS-IV results, we also report the OLS results for comparison. We used a Hausman test as an additional aid in determining the necessity of the IV approach. Two tests were applied to the full US sample. The first test was run on the β^* 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. Both tests reject the null hypothesis at the 1% level, suggesting that the OLS estimates are indeed inconsistent, and confirming the importance of using the IV method for addressing the potential endogeneity of conditioning variables.[10]

We follow Rappaport and Sachs (2003), Rappaport (2005) and Higgins, et al. (2006) in accounting for a possible spatial correlation between the error-terms of the counties located in proximity with each other. We report 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. These results are reported as "CR-OLS" (Conley-Rappaport-OLS) in Tables 2, 4 and 5.

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[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. Indeed, we have estimated the model using a panel-GMM method of Caselli, et al. (1996) but the resulting estimates did not make much sense. We believe the main reason for the failure of the panel-GMM approach is that it is 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.

[10] Some of the variables we use could be viewed as endogenous. We believe, however, that the problem is not severe because in our model, the right-hand side (RHS) variables are temporally prior to the regressors. Also, we use instrumental variables (IVs) to account for the endogeneity. Indeed, the Hausman test confirmed the appropriateness of the IV approach.

Rappaport and Sachs specify a cutoff distance $\bar{d}$, and assume that the covariance between the errors of two counties is zero, if the 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*. It is assumed that $E(\varepsilon_i \varepsilon_j) = g(d_{ij})\rho_{ij}$, where $\hat{\rho}_{ij} = e_i e_j$, and $g(d_{ij}) = 1$ for $d_{ij} = 0$, $g(d_{ij}) = 0$ for $d_{ij} > \bar{d}$, and $g'(d_{ij}) \leq 0$ for $d_{ij} \leq \bar{d}$. Consistent with Rappaport (1999 and 2005), Rappaport and Sachs (2003), and Higgins, et al. (2006), we assume that the covariance between the error terms drops quadratically as the distance between the counties increases to $\bar{d} = 200\text{km}$.

B. US county-level data

The data we use are drawn from several sources but the majority comes from the Bureau of Economic Analysis Regional Economic Information System (BEA-REIS) and US 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 all data.

Our data contain 3,058 county-level observations. **Figure 1** displays the US divided into counties.[11] The large number of observations allows us to explore possible heterogeneity in growth experiences across the US by splitting the data into three sets of sub-samples. The first set separates the data into 867 metro and 2,191 non-metro

[11] The figure excludes Hawaii and Alaska, but these counties are included in the full and regional samples.

counties.[12] Given the large sample, the sub-sample analysis sacrifices little in terms of degrees of freedom. The second set combines counties into geographic regions: Great Lakes, Northeast, Southern, Plains, and Western. Finally, the third set parses the counties up into their respective 50 US state sub-samples.[13]

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, we utilize 38 demographic conditioning variables, listed in **Table 1**.[14]

IV. Empirical findings

A. Full US sample results

Table 2 presents the estimation results for the full US sample, as well as metro and non-metro samples. Utilizing 3SLS-IV estimation (the results of which we focus on) we find a negative and statistically significant partial correlation between the percent of the population employed in the public sector and the rate of economic growth, regardless of whether one considers federal, state or local government. Moreover, there is no clear pattern in the point estimates of partial correlations as the level of decentralization increases; and the 95 percent confidence intervals all overlap. The coefficients for the federal, state and local employee percent of the population variables are –0.0226, –0.0177, and –0.0198 respectively, all significant at the 1-percent level.

[12] Following Higgins, et al. (2006) who follow the definition used by the Census Bureau, metro counties are defined as those that contain cities with populations of 100,000 or more, or border such counties. See Census Bureau publication SU-99-1, "Population Estimates for Cities with Populations of 100,000 and Greater."
[13] Due to the extensive number of independent variables the model is only specified for 32 of 50 states.
[14] An appendix at the end of the paper describes the data in more detail.

This relationship, however, might be nonlinear. Government to a certain extent might be good for growth, but then becomes a negative influence as it expands further. For example, "with low tax rates, the positive effect of public production services on the productivity of private capital stocks exceeds the negative effect of [a] distortionary tax on private capital accumulation" (Park, 2005, p. 10). Or it may be the case that government activities may be aimed at enhancing growth up to a point but then further activities, at the margin, may then aim at redistribution of income for equity concerns (Buchanan and Wagner, 1977).[15] Yet another possibility is that there are certain goods and services which the government provides and which are essential for efficient functioning of the economy (e.g., legal and law enforcement institutions, public roads, airports). As long as the labor force employed by the government is involved in the production of such goods and services, government expenditures can be growth promoting. Expanding the size and the scope of the government beyond this, however, may be growth-hindering.

To check this possibility of a nonlinear relationship, we run the full US sample 3SLS-IV regressions with both linear and quadratic terms. We include $\gamma_{fl}F + \gamma_{sl}S + \gamma_{ll}L + \gamma_{fs}(F)^2 + \gamma_{ss}(S)^2 + \gamma_{ls}(L)^2$ in the regression model, where *F*, *S*, and *L* are the percent of population employed by federal, state, and local governments, respectively. With the quadratic terms, the marginal effect of the federal government variable, for example, 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 on the quadratic term would

[15] Our analysis does not allow us to explicitly separate out redistributive activities of government. If negative effects of government on growth are to be excused in terms of a tradeoff with income inequality then we would expect redistributive efforts bear fruit. This is addressed in more detail in Section IV(C).

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 percent and 5 percent levels, respectively, we obtain $\partial g / \partial F = -0.0331 + 2(0.0477)(F)$, which, after setting equal to zero, implies that marginal additions to F are negatively correlated with g for F values up until 0.35 (until the federal government employs over 35 percent 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 percent of the population). Such F values, however, are unreasonable for the US.[16] For realistic values, federal government employment (as well as state and local) is negatively correlated with economic growth.

The negative effects are also present at all levels of government employment whether one considers only metro counties or only non-metro counties as indicated by the figures in **Table 2**. This suggests that government employment is not positively related to economic growth at higher population densities. Indeed the negative partial correlations are larger for the metro sample than for the non-metro sample at all levels.

While these findings may suggest that an increased public sector hinders economic growth via distortion of incentives and diversion of resources, another possible interpretation is that non-government wage growth simply outpaces government wage

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

growth, and this drives the result.[17] In order to explore this alternative explanation we have assembled government and non-government wage growth data for the sample period. At the state and federal level, **Table 3** demonstrates that across the entire sample non-government wages outpace government wages in approximately 55 percent (a small majority) of counties. At the local level, non-government wages grew faster in only about 30 percent of counties. Relative sluggishness of government wages at the state and federal levels is dominated by wage growth rates in the metro counties. For the non-metro counties, which constitute a vast majority of 2,196 counties panel, non-government wages outpaced government wages in just over 50 percent of cases.[18]

If a relatively sluggish growth of government wages story were important, then we would expect to find smaller estimated coefficients for metro counties than for non-metro counties. This we do see. The coefficient estimates for the regression including only metro counties are –0.0300, –0.0264 and –0.0214 for federal, state and local governments respectively. For non-metro counties the corresponding estimates are –0.0179, –0.0081 and –0.0128. Note, however, that this pattern holds for the local government coefficients as well, despite local wages outpacing non-government wages in a majority of counties. At least at the most decentralized level of government, a relatively sluggish government wage growth story is unable to account for the negative partial correlation. Indeed, we estimate a negative relationship *despite the relatively fast growth of government wages*.

B. Regional Results and Individual State Results

[17] We thank Paul Rubin for bringing this possibility to our attention.

[18] Table 3 utilizes data from 3,066 counties. Our regression analysis utilizes data for only 3,058 counties. The difference is due to a lack of some data in eight counties.

Table 4 reports the results for our five regional sub-samples: Great Lakes, Northeastern, Southern, Plains and Western. These results are broadly consistent with our main country-wide findings. All statistically significant coefficient estimates except those associated with the non-metro Plains region are negative. The statistically significant coefficient estimates that are negative occur, variously, for federal, state, and local government. Many of the coefficient estimates are statistically insignificant. Thus, the findings from the regional sub-samples suggest that government employment, at all three levels of disaggregation (federal, state, and local), is either negatively correlated with or is uncorrelated with economic growth.

While not relevant for the full sample (see Section *A* above), the non-metro Plains region effects may be an artifact of the government relative to non-government wage growth. Federal, state, and local government wage growth, respectively, outpaced non-government wage growth in approximately 62 percent, 68 percent, and 80 percent of counties. The relatively high growth in government wages may account for the estimated positive effect of government employment on income growth.

Table 5 reports the estimates for 32 of 50 individual US state sub-samples.[19] Again, these results are broadly consistent with the conclusion that government employment, at all three levels, is either negatively correlated with or is uncorrelated with economic growth. We find two exceptions to these broad findings. First, the local government employment coefficient for Kansas is positive and significant at the 10 percent level. (Kansas ranked 8th highest amongst states in terms of local government employment with 4.2 percent.) Second and a more notable exception is North Dakota.

[19] Given the extensive number of independent variables, our model was only identified in 32 of 50 states. By this we refer to the coefficient on initial income being statistically significant. In the absence of this the interpretation of conditioning variable coefficients is unclear.

North Dakota has large coefficients on federal, state, and local government employment, all significant at the 5 percent level or better.

It is not immediately apparent what might be peculiar about North Dakota. For example, in 1970, North Dakota ranked 21st highest in terms of federal government employment (1.3 percent); 7th in terms of state government employment (2.3 percent); and 4th in terms of local government employment (4.7 percent). However, similar to the Plains region non-metro case, federal, state, and local government wage growth was higher than non-government wage growth in, respectively, about 57 percent, 75 percent, and 85 percent of counties. This exceptional government relative wage growth may account for the estimated positive effect of government employment on income growth.

C. Are Redistributive Activities Driving the Results?

As mentioned previously, it is possible that the negative correlation between government employment and economic growth is due to the redistributive activities of government. Redistributive activities may be detrimental towards average (per capita) income growth. Furthermore, if greater income equality is valued in and of itself, then trading off that growth may even be viewed as desirable.

Our analysis cannot separate out the productive and redistributive activities of federal, state, or local governments. However, under the hypothesis that the negative correlation (or the lack of correlation) between government employment and economic growth is due to redistributive activities, we can ask whether or not the economic growth has indeed been traded off for a more equitable distribution of income. This will be informative as to whether the negative correlation is meaningful. In other words, we can evaluate a possible redistributive role for the various levels of government *given the caveat* that we do not control for how the distribution of income might have evolved in the absence of government.

Figure 2 displays the 1970 and 1998 distributions of per capita income across US states.[20] The distribution has become wider over time. On the other hand we can consider the Gini coefficients associated with the county-level income distribution in 1970 and 1998. The Gini coefficient associated with US counties' 1970 and 1998 (log) income is 0.0167 and 0.0165 respectively – a decrease of about 1.2 percent.[21]

Interestingly, at the county-level, although the dispersion of US per capita income widened from 1970 to 1998, it became a bit more equal.[22] However, changes in both the standard deviation and the Gini coefficient are small enough to suggest that both dispersion and equality remained essentially the same.

To try to understand further the evolution of the US county-level income distribution, **Table 6** summarizes statistics computed from the 1970 and 1998 income distributions. From 1970 to 1998, the skewness of the distribution increased from -0.2244 (to the left) to 1.7240 (to the right). At the same time, kurtosis increased from 3.4334 to 10.3237, implying that the distribution has become more peaked. Cumulatively, this suggests that these two effects have been offsetting to a great extent.

In conclusion, we find no obvious evidence that government activities have achieved (absolutely) a more equal distribution of income at the expense of lower rates of economic growth.

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[20] See Young, et al. (2006) for a discussion of this evolving distribution of income in relation to the apparent conditional (beta) convergence that empirical studies typically detect in the US economy.
[21] The Gini coefficient is a number between 0 (perfect equality) and 1 (perfect inequality).
[22] This statement is not to be confused with one concerning the distribution of US *individuals' incomes.*

V. Concluding Remarks

We use a recently assembled US county-level data containing over 3,000 cross-sectional observations during the period 1970 to 1998 to explore the relationships between economic growth and the size of government at three levels: federal, state and local. In contrast to the extant literature (Atkinson, 1995; Slemrod, 1995; Agel, et al., 1997; and, Rodrik, 2005) that has used taxes, government expenditures and government capital stocks to proxy for the extent of government, here we use a direct measure – the percent of a county's labor force that is under the direction of government.

Following Higgins, et al. (2006), we use a 3SLS-IV estimation technique and report on full sample, metro region, non-metro region, five regional and 32 individual state samples. We find that the size of federal, state and local government all negatively correlate with economic growth in the full samples, as well as in the overwhelming majority of regional and state samples (when statistical significance holds).

We find no evidence that government is more effective at more or less decentralized levels. Furthermore, while we cannot separate out the productive and redistributive services of government, we document that income inequality in the US has widened slightly from 1970 to1998. However, the change in both the standard deviation of per capita income and the Gini coefficient are small enough to suggest that both dispersion and equality remained essentially the same.[23]

[23] A reader might question the applicability of the neoclassical growth model to the US counties. We agree that the model may not be the most suitable framework for thinking about growth in US counties given their extraordinary degree of openness. Rappaport (1999, 2004, 2005, and 2006) proposes a way around this problem by offering a version of the model for studying local growth, where by "local" is meant small open economic units comprising a larger entity, such as counties comprising the US The distinguishing characteristic of small open economies such as US counties is the extraordinary mobility of labor. The

Given the ostensible goals of higher growth and/or a more equitable distribution of income, our findings are not supportive of expanding the roles of government, in terms of employment, at any level. The US government use of the labor force seems to be either unproductive or growth-hindering at all three levels of decentralization. Taken at face value, our findings seem to suggest for a rolling back of government activities; specifically for a release of government-employed labor inputs to the private sector.

question Rappaport asks is how does labor mobility affects convergence. Rappaport (1999, 2005) expands the model by allowing labor mobility and finds that the model predicts conditional convergence, which is what Higgins, et al. (2006) find.

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).[24] 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

[24] 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.

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 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.[25]

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

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[25] 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.

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.

Given the data constraints, it was necessary to use an interpolation procedure for some variables.[26] In this study we cover the 1970 to 1998 period. However, in order to implement the Evans' (1997a, 1997b) 3SLS estimation method, we needed to have available data values for 1969 and 1997. We used a linear interpolation method 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.

[26] Given the cross-section nature of our data, the use of interpolation does not cause problems of the type reported by Dezhbakhsh and Levy (1994) in their study of periodic properties of interpolated time series.

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Table 1. Variable Definitions and Sources

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	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
Poverty	Percent of the population below the poverty line	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
Entertainment & Recreational Services	Percent of population employed in entertainment & recreational services	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
Transportation	Percent of the population employed in transportation		
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
Personal services	Percent of population employed in personal services	1970-1990	Census
Wholesale trade	Percent 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

Note: All BEA variables are available annually from 1969 to 1998. The Census variables are gathered from the 1970, 1980 and 1990 Census tapes.

Table 2. Estimated Effects of Federal, State and Local Government on US Economic Growth (Entire US, Metro, and Non-Metro)

Variable	OLS Coefficient	CR-OLS Coefficient	3SLS Coefficient
Entire US			
Federal government employment	-0.0145 (0.0048)[a]	-0.0145 (0.0046)[a]	-0.0226 (0.0051)[a]
State government employment	-0.0040 (0.0037)	-0.0040 (0.0045)	-0.0177 (0.0040)[a]
Local government employment	-0.0211 (0.0048)[a]	-0.0211 (0.0079)[a]	-0.0198 (0.0052)[a]
Metro region			
Federal government employment	-0.0095 (0.0098)	-0.0095 (0.0105)	-0.0300 (0.0107)[a]
State government employment	-0.0058 (0.0071)	-0.0058 (0.0049)	-0.0264 (0.0076)[a]
Local government employment	-0.0141 (0.0108)	-0.0141 (0.0117)	-0.0214 (0.0120)[c]
Non-metro region			
Federal government employment	-0.0137 (0.0056)[b]	-0.0137 (0.0049)[a]	-0.0179 (0.0060)[a]
State government employment	0.0021 (0.0004)	0.0021 (0.0064)	-0.0081 (0.0048)[c]
Local government employment	-0.0165 (0.0055)[a]	-0.0165 (0.0087)[c]	-0.0128 (0.0059)[b]

Standard errors are reported in parentheses. “CR” denotes a generalization of the Huber-White heteroskedastic-consistent standard error estimator based on Rappaport’s (1999) implementation of Conley’s (1999) correction which produces standard errors that are robust to a spatial correlation. See the text for details.

[a] Significant at the 1% level.
[b] Significant at the 5 % level.
[c] Significant at the 10% level.

Table 3. Government versus Non-Government Wage Growth Data, 1970 to 1998

(a) All Counties (3,066 counties)

Level	Non-Government[1]>Government	Government>Non-Government	% counties where growth of government wages are greater than growth of non-government wages
Federal	1,706	1,360	44.36%
State	1,675	1,391	45.37%
Local	909	2,157	70.35%

(b) Metro Counties (870 counties)

Level	Non-Government>Government	Government>Non-Government	% counties where growth of government wages are greater than growth of non-government wages
Federal	573	297	34.14%
State	532	338	38.85%
Local	364	506	58.16%

(c) Non-Metro Counties (2,196 counties)

Level	Non-Government>Government	Government>Non-Government	% counties where growth of government wages are greater than growth of non-government wages
Federal	1133	1063	48.41%
State	1143	1053	47.95%
Local	545	1651	75.18%

[1] Non-government wages are the sum of private and farm wages.

Table 4. Estimated Effects of Federal, State, and Local Government on US Regional Economic Growth

Panel A: Federal Government Employment

Region	Area	Number of Counties	OLS	CR-OLS	3SLS
Great Lakes	All counties	435	-0.0004 (0.0147)	-0.0004 (0.0081)	-0.0029 (0.0152)
Great Lakes	Metro counties	140	0.0353 (0.0315)	0.0353 (0.0136)	0.0114 (0.0343)
Great Lakes	Non-metro counties	295	0.0074 (0.0192)	0.0074 (0.0057)	0.0110 (0.0194)
Northeast	All counties	244	-0.0118 (0.0184)	-0.0118 (0.0094)	-0.0252 (0.0205)
Northeast	Metro counties	90	0.0303 (0.0321)	0.0303 (0.0171)[c]	0.0163 (0.0357)
Northeast	Non-metro counties	154	-0.0112 (0.0231)	-0.0112 (0.0061)[c]	-0.0267 (0.0252)
Plains	All counties	832	-0.0201 (0.0101)	-0.0201 (0.0100)	-0.0261 (0.0103)[b]
Plains	Metro counties	143	-0.0200 (0.0253)	-0.0200 (0.0077)[a]	-0.0139 (0.0283)
Plains	Non-metro counties	689	-0.0182 (0.0114)	-0.0182 (0.0120)	0.0187 (0.0102)[c]
Southern	All counties	1,009	-0.0132 (0.0081)[c]	-0.0132 (0.0054)[b]	-0.0207 (0.0090)[b]
Southern	Metro counties	252	-0.0212 (0.0199)	-0.0212 (0.0097)[b]	-0.0345 (0.0211)[c]
Southern	Non-metro counties	757	-0.0127 (0.0092)	-0.0127 (0.0073)[c]	-0.0131 (0.0103)
Western	All counties	538	-0.0134 (0.0105)	-0.0134 (0.0081)[c]	-0.0166 (0.0113)
Western	Metro counties	242	0.0002 (0.0190)	0.0002 (0.0161)	-0.0108 (0.0223)
Western	Non-metro counties	296	-0.0081 (0.0143)	-0.0081 (0.0083)	-0.0103 (0.0149)

Panel B: State Government Employment

Region	Area	Number of Counties	OLS	CR-OLS	3SLS
Great Lakes	All counties	435	-0.0116 (0.0093)	-0.0116 (0.0059)[b]	-0.0181 (0.0096)[c]
Great Lakes	Metro counties	140	0.0015 (0.0199)	0.0015 (0.0049)	-0.0203 (0.0214)
Great Lakes	Non-metro counties	295	-0.0188 (0.0110)[c]	-0.0188 (0.0063)[a]	-0.0223 (0.0115)[c]
Northeast	All counties	244	0.0009 (0.0121)	0.0009 (0.0060)	-0.0094 (0.0135)
Northeast	Metro counties	90	-0.0106 (0.0267)	-0.0106 (0.0110)	-0.0172 (0.0299)
Northeast	Non-metro counties	154	0.0124 (0.0139)	0.0124 (0.0033)[a]	0.0048 (0.0153)
Plains	All counties	832	0.0132 (0.0076)[c]	0.0132 (0.0075)[c]	0.0063 (0.0077)
Plains	Metro counties	143	-0.0178 (0.0140)	-0.0178 (0.0145)	-0.0356 (0.0152)[b]
Plains	Non-metro counties	689	0.0274 (0.0088)[a]	0.0274 (0.0083)[a]	0.0161 (0.0092)[c]
Southern	All counties	1,009	0.0062 (0.0068)	0.0062 (0.0059)	-0.0047 (0.0075)
Southern	Metro counties	252	0.0027 (0.0171)	0.0027 (0.0087)	-0.0153 (0.0179)
Southern	Non-metro counties	757	0.0043 (0.0076)	0.0043 (0.0055)	-0.0042 (0.0085)
Western	All counties	538	-0.0010 (0.0096)	-0.0010 (0.0087)	-0.0148 (0.0101)
Western	Metro counties	242	-0.0040 (0.0137)	-0.0049 (0.0113)	-0.0206 (0.0160)
Western	Non-metro counties	296	0.0124 (0.0148)	0.0124 (0.0107)	-0.0037 (0.0154)

Table 4. Estimated Effects of Federal, State, and Local Government on US Regional Economic Growth (continued)

Panel C: Local Government Employment

Region	Area	Number of Counties	OLS	CR-OLS	3SLS
Great Lakes	All counties	435	-0.0362 (0.0125)[a]	-0.0362 (0.0038)[a]	-0.0343 (0.0129)[a]
Great Lakes	Metro counties	140	-0.0540 (0.0362)	-0.0540 (0.0135)	-0.0332 (0.0397)
Great Lakes	Non-metro counties	295	-0.0345 (0.0143)[b]	-0.0345 (0.0061)[a]	-0.0331 (0.0145)[b]
Northeast	All counties	244	-0.0261 (0.0235)	-0.0261 (0.0169)	-0.0430 (0.0261)[c]
Northeast	Metro counties	90	-0.0510 (0.0564)	-0.0510 (0.0189)	-0.1151 (0.0595)[c]
Northeast	Non-metro counties	154	-0.0300 (0.0304)	-0.0300 (0.0146)	-0.0476 (0.0332)
Plains	All counties	832	0.0001 (0.0084)	0.0001 (0.0115)	0.0048 (0.0086)
Plains	Metro counties	143	-0.0156 (0.0200)	-0.0156 (0.0162)	-0.0066 (0.0223)
Plains	Non-metro counties	689	0.0101 (0.0098)	0.0101 (0.0125)	0.0187 (0.0102)[c]
Southern	All counties	1,009	0.0032 (0.0100)	0.0032 (0.0051)	0.0008 (0.0110)
Southern	Metro counties	252	-0.0001 (0.0327)	-0.0001 (0.0155)	0.0041 (0.0349)
Southern	Non-metro counties	757	0.0066 (0.0104)	0.0066 (0.0046)	0.0061 (0.0116)
Western	All counties	538	-0.0243 (0.0115)[b]	-0.0243 (0.0081)[a]	-0.0293 (0.0123)[b]
Western	Metro counties	242	-0.0114 (0.0194)	-0.0114 (0.0200)	-0.0397 (0.0224)[c]
Western	Non-metro counties	296	-0.0263 (0.0164)[c]	-0.0263 (0.0095)[a]	-0.0270 (0.0173)

Standard errors are reported in parentheses. "CR" denotes a generalization of the Huber-White heteroskedastic-consistent standard error estimator based on Rappaport's (1999) implementation of Conley's (1999) correction which produces standard errors that are robust to a spatial correlation. See the text for details.

[a] significant at 1% level
[b] significant at 5% level
[c] significant at 10% level

Table 5. Estimated Effects of Federal, State, and Local Government on Growth in 32 Individual States

Region	Federal Government Employment			State Government Employment			Local Government Employment		
	OLS	CR-OLS	3SLS	OLS	CR-OLS	3SLS	OLS	CR-OLS	3SLS
United States	-0.0145 (0.0048)[a]	-0.0145 (0.0046)[a]	-0.0226 (0.0051)[a]	-0.0040 (0.0037)	-0.0040 (0.0045)	-0.0177 (0.0040)[a]	-0.0211 (0.0048)[a]	-0.0211 (0.0079)[a]	-0.0198 (0.0025)[a]
Alabama	0.0327 (0.0635)	0.0327 (0.0013)[a]	0.0434 (0.0577)	-0.0473 (0.0595)	-0.0473 (0.0028)[a]	-0.0514 (0.0579)	0.0221 (0.0573)	0.0221 (0.0019)[a]	0.0225 (0.0565)
Arkansas	-0.0085 (0.0503)	-0.0085 (0.0029)[a]	-0.0119 (0.0514)	-0.0164 (0.0393)	-0.0164 (0.0012)[a]	-0.0251 (0.0398)	-0.0424 (0.0494)	-0.0424 (0.0023)[a]	-0.0242 (0.0493)
California	0.0321 (0.0312)	0.0321 (0.0011)[a]	0.0322 (0.0304)	0.0134 (0.0488)	0.0134 (0.0031)[a]	0.0141 (0.0455)	-0.0148 (0.0992)	-0.0148 (0.0018)[a]	-0.0137 (0.0943)
Colorado	-0.0249 (0.0389)	-0.0249 (0.0022)[a]	-0.0643 (0.0451)	-0.0338 (0.0384)	-0.0338 (0.0024)[a]	-0.0729 (0.0346)[c]	-0.0174 (0.0339)	-0.0174 (0.0026)[a]	-0.0362 (0.0404)
Florida	0.0821 (0.0821)	0.0821 (0.0035)[a]	0.0686 (0.0888)	0.0100 (0.0585)	0.0100 (0.0042)[b]	0.0223 (0.0632)	-0.0228 (0.0894)	-0.0228 (0.0023)[a]	0.0235 (0.0947)
Georgia	0.0309 (0.0339)	0.0309 (0.0015)[a]	0.0078 (0.0365)	0.0301 (0.0232)	0.0301 (0.0013)[a]	0.0193 (0.0251)	0.0477 (0.0289)[c]	0.0477 (0.0032)[a]	0.0294 (0.0312)
Idaho	-0.1485 (0.0881)[c]	-0.1485 (0.0043)[a]	-0.1368 (0.0648)[c]	0.0552 (0.0586)	0.0552 (0.0022)[a]	0.0458 (0.0365)	0.0379 (0.1142)	0.0379 (0.0060)[a]	0.0197 (0.0713)
Illinois	0.0478 (0.0325)	0.0478 (0.0018)[a]	0.0487 (0.0322)	0.0034 (0.0195)	0.0034 (0.0007)[a]	0.0034 (0.0193)	0.0071 (0.0240)	0.0071 (0.0017)[a]	0.0071 (0.0238)
Indiana	-0.0969 (0.0491)[b]	-0.0969 (0.0011)[a]	-0.0586 (0.0357)	0.0324 (0.0278)	0.0324 (0.0009)[a]	0.0009 (0.0297)	-0.0311 (0.0381)	-0.0311 (0.0015)[a]	-0.0311 (0.0381)
Iowa	0.0605 (0.0392)	0.0605 (0.0018)[a]	0.0607 (0.0389)	-0.0414 (0.0236)[b]	-0.0414 (0.0014)[a]	-0.0423 (0.0231)[b]	0.0124 (0.0273)	0.0124 (0.0015)[a]	0.0137 (0.0265)
Kansas	0.0281 (0.0394)	0.0281 (0.0024)[a]	0.0278 (0.0393)	0.0130 (0.0173)	0.0130 (0.0011)[a]	0.0113 (0.0171)	0.0329 (0.0183)[c]	0.0329 (0.0012)[a]	0.0337 (0.0182)[c]
Kentucky	-0.0080 (0.0232)	-0.0080 (0.0018)[a]	-0.0058 (0.0023)	0.0155 (0.0200)	0.0155 (0.0016)[a]	0.0133 (0.0200)	0.0026 (0.0253)	0.0026 (0.0016)[a]	-0.0001 (0.0253)
Louisiana	-0.0428 (0.0309)	-0.0428 (0.0008)[a]	-0.0131 (0.0057)	-0.0024 (0.0282)	-0.0024 (0.0012)[b]	-0.0130 (0.0336)	-0.1463 (0.0500)[a]	-0.1463 (0.0030)[a]	-0.1792 (0.0589)[a]
Michigan	0.0442 (0.0435)	0.0442 (0.0027)[a]	0.0740 (0.0500)	-0.0091 (0.0291)	-0.0091 (0.0007)[a]	-0.0566 (0.0313)[c]	-0.0100 (0.0335)	-0.0100 (0.0023)[a]	-0.0478 (0.0376)
Minnesota	-0.1118 (0.0633)[c]	-0.1118 (0.0028)[a]	-0.0783 (0.0645)	0.0217 (0.0247)	0.0217 (0.0015)[a]	0.0048 (0.0247)	-0.0461 (0.0235)[b]	-0.0461 (0.0013)[a]	-0.0431 (0.0246)[c]
Mississippi	-0.0521 (0.0591)	-0.0521 (0.0017)[a]	-0.0180 (0.0626)	-0.0333 (0.0508)	-0.0333 (0.0025)[a]	-0.0303 (0.0494)	-0.0467 (0.0675)	-0.0467 (0.0037)[a]	-0.1325 (0.0660)[b]
Missouri	-0.0547 (0.0269)[b]	-0.0547 (0.0021)[a]	-0.0917 (0.0320)[a]	-0.0292 (0.0210)	-0.0292 (0.0018)[a]	-0.0655 (0.0244)[a]	-0.0243 (0.0244)	-0.0243 (0.0028)[a]	-0.0205 (0.0298)
Montana	-0.0481 (0.0650)	-0.0481 (0.0097)[a]	-0.0739 (0.0632)	0.0457 (0.0493)	0.0457 (0.0108)[a]	0.0144 (0.0440)	0.0288 (0.0500)	0.0288 (0.0059)[a]	0.0260 (0.0508)
New York	0.0254 (0.1075)	0.0254 (0.0036)[a]	0.0852 (0.1233)	0.0257 (0.0402)	0.0257 (0.0023)[a]	0.0609 (0.0450)	-0.0314 (0.0712)	-0.0314 (0.0042)[a]	-0.0362 (0.0831)
North Carolina	-0.0570 (0.0544)[c]	-0.0570 (0.0038)[a]	-0.1263 (0.0648)	-0.0129 (0.0238)	-0.0129 (0.0021)[a]	-0.0422 (0.0285)	0.0166 (0.0467)	0.0166 (0.0048)[a]	-0.0101 (0.0568)
North Dakota	0.1636 (0.0988)[c]	0.1636 (0.0098)[a]	0.2348 (0.1126)[b]	0.1326 (0.0691)[c]	0.1326 (0.0051)[a]	0.1604 (0.0811)[b]	0.2070 (0.0782)[a]	0.2070 (0.0086)[a]	0.2491 (0.0910)[a]
Ohio	-0.0307 (0.0567)	-0.0307 (0.0043)[a]	-0.0263 (0.0574)	-0.0072 (0.0263)	-0.0072 (0.0018)[a]	-0.0155 (0.0261)	-0.0219 (0.0499)	-0.0219 (0.0018)[a]	-0.0002 (0.0485)
Oklahoma	-0.1130 (0.0506)[b]	-0.1130 (0.0080)[a]	-0.1065 (0.0520)[b]	-0.0366 (0.0357)	-0.0366 (0.0019)[a]	-0.0467 (0.0364)	-0.0789 (0.0416)[c]	-0.0789 (0.0023)[a]	-0.0880 (0.0426)[b]
Pennsylvania	0.0264 (0.0577)	0.0264 (0.0028)[a]	0.0267 (0.0285)	0.0577 (0.0287)[b]	0.0577 (0.0018)[a]	0.0620 (0.0283)	-0.1015 (0.0593)[c]	-0.1015 (0.0038)[a]	-0.1000 (0.0592)
South Carolina	-0.0582 (0.1065)	-0.0582 (0.0040)[a]	-0.0520 (0.1028)	0.0183 (0.1384)	0.0183 (0.0042)[a]	-0.0280 (0.1163)	-0.0334 (0.1454)	-0.0334 (0.0115)[a]	-0.0270 (0.1406)
South Dakota	-0.0144 (0.0454)	-0.0144 (0.0031)[a]	-0.0384 (0.0424)	-0.0043 (0.0323)	-0.0043 (0.0019)[b]	-0.0057 (0.0453)	0.0063 (0.0455)	0.0063 (0.0019)[a]	-0.0057 (0.0453)
Tennessee	0.0110 (0.0321)	0.0110 (0.0062)[c]	0.0054 (0.0353)	-0.0267 (0.0330)	-0.0267 (0.0027)[a]	-0.0566 (0.0352)	0.0022 (0.0336)	0.0022 (0.0021)	0.0059 (0.0370)
Texas	-0.0551 (0.0302)[c]	-0.0551 (0.0039)[a]	-0.0378 (0.0318)	0.0053 (0.0178)	0.0053 (0.0024)[b]	-0.0007 (0.0188)	-0.0252 (0.0210)	-0.0252 (0.0033)[a]	-0.0271 (0.0222)
Virginia	-0.0088 (0.0346)	-0.0088 (0.0022)[a]	0.0053 (0.0404)	0.0390 (0.0413)	0.0390 (0.0027)[a]	0.0310 (0.0484)	0.0471 (0.0466)	0.0471 (0.0033)[a]	0.0261 (0.0543)
Washington	-0.0249 (0.0551)	-0.0249 (0.0031)[a]	-0.0085 (0.0885)	0.0167 (0.1323)	0.0167 (0.0065)[b]	-0.0085 (0.0885)	0.1718 (0.3523)	0.1718 (0.0132)[a]	-0.0502 (0.5439)
West Virginia	0.0571 (0.0653)	0.0571 (0.0032)[a]	0.0980 (0.0810)	-0.0060 (0.0413)	-0.0060 (0.0019)[a]	-0.0185 (0.0519)	-0.0605 (0.0788)	-0.0605 (0.0041)[a]	-0.0067 (0.0975)
Wisconsin	-0.0087 (0.0364)	-0.0087 (0.0028)[a]	-0.0017 (0.0358)	-0.0444 (0.0343)	-0.0444 (0.0038)[a]	-0.0375 (0.0337)	0.0191 (0.0400)	0.0191 (0.0021)[a]	0.0264 (0.0394)

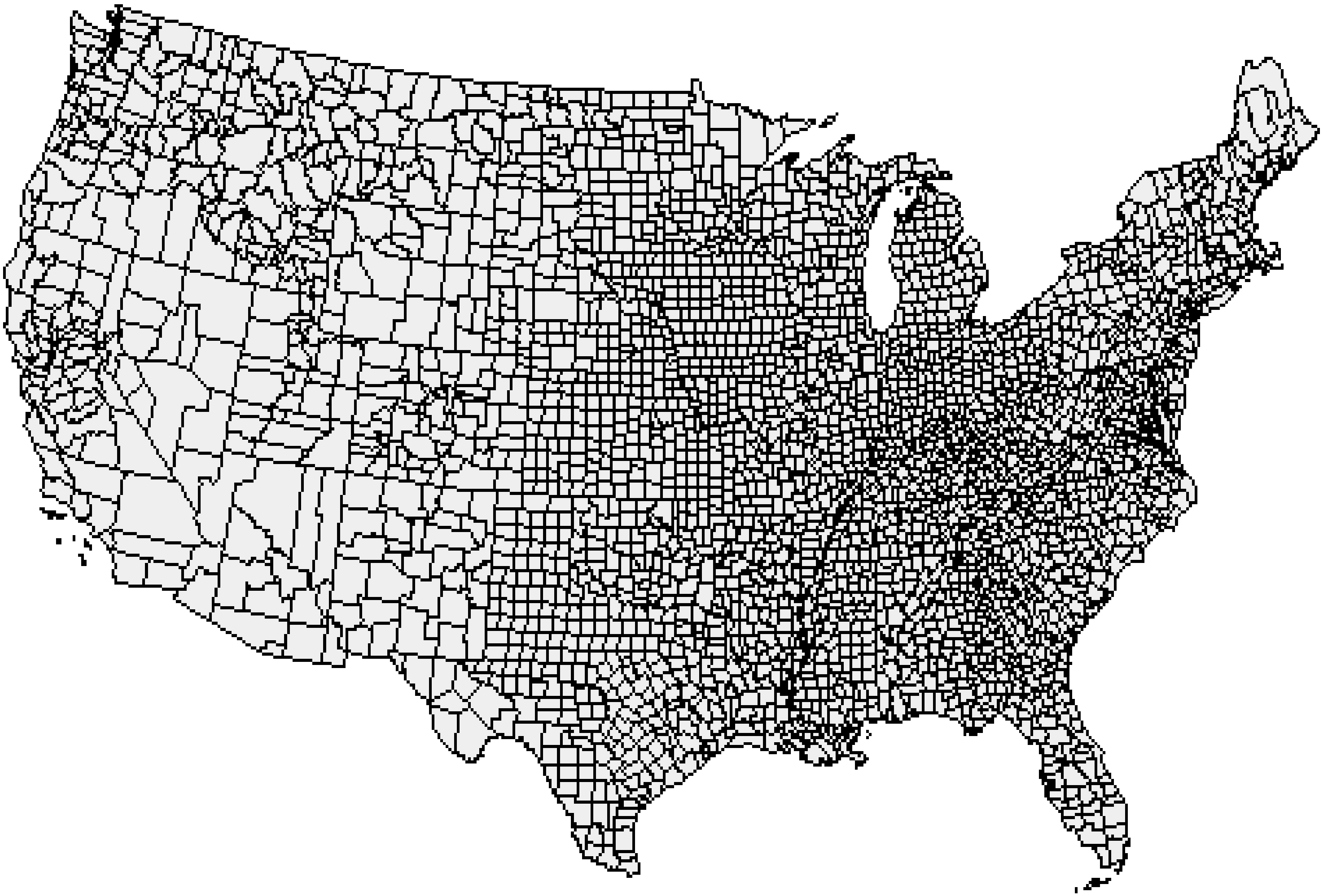
Standard errors are reported in parentheses. "CR" denotes a generalization of the Huber-White heteroskedastic-consistent standard error estimator based on Rappaport's (1999) implementation of Conley's (1999) correction which produces standard errors that are robust to a spatial correlation. See the text for details.

[a] Significant at the 1% level.
[b] Significant at the 5 % level.
[c] Significant at the 10% level.

Table 6. Summary Statistics for Distribution of US Counties' Log Per Capita Incomes

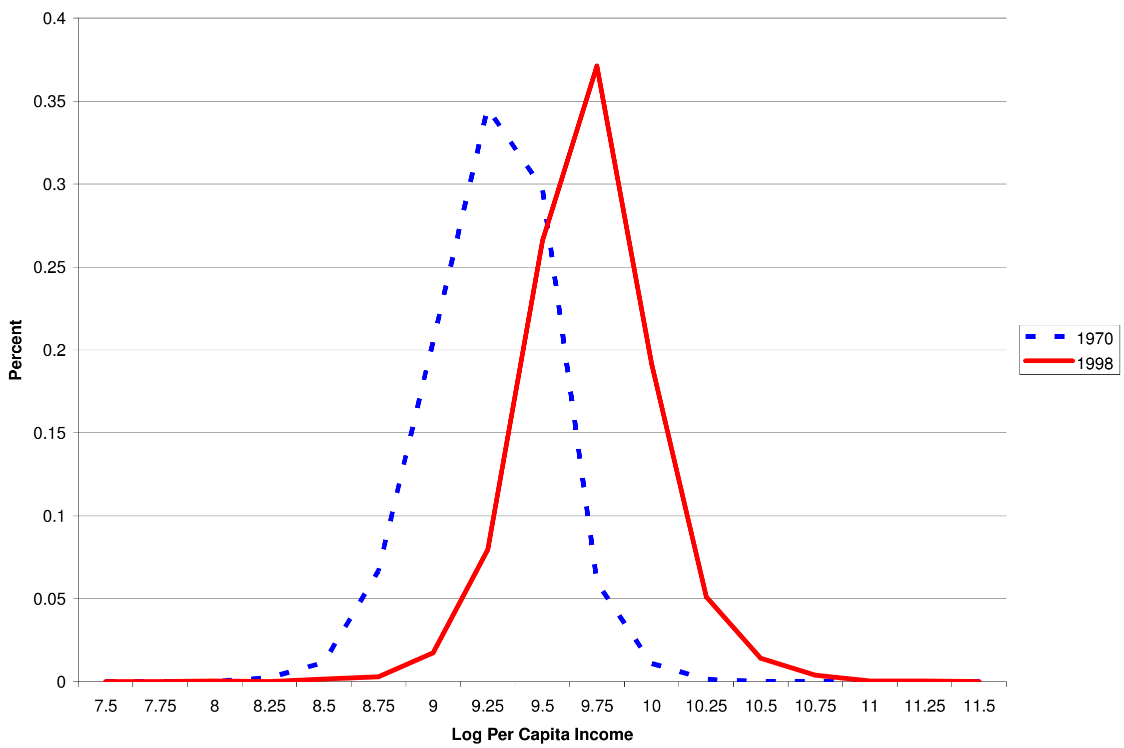
Statistic	1970 Per Capita Income	1998 Per Capita Income
Standard Deviation	0.2728	0.2887
Gini Coefficient	0.1666	0.1654
Skewness	-0.2244	1.7240
Kurtosis	3.4334	10.3237

Figure 1. 3,058 U.S.A Counties



Note: Hawaiian and Alaskan counties are not shown.

Figure 2. Distribution of US Counties' Log Per Capita Incomes, 1970 and 1998



Referee's Appendix: Inconsistency of OLS Estimates

The method of ordinary least squares (OLS) could be used to infer the values of β and γ in equation (3). However, Evans (1997b) states that the OLS estimates obtained from (3) are unlikely to be consistent.[1] 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 ε_{nt} is a zero-mean, covariance stationary error process independently distributed over time and across economies. The error term, ε_{nt}, is uncorrelated with x_n, λ_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 λ_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 Δa_t is covariance stationary and independent of ε_{nt}.

The common trend a_t for all the y variables will be the sole catalyst of economic growth in all economies if λ_n<1. In this case, growth is exogenous and economies would follow a balanced-growth path. If λ_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 δ_n controls for the relative height of economy n's balanced growth path if all the λs are less than one. If $\lambda_n = 1$, then δ_n controls for economy n's

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

relative growth rate. The error term ω_n measures the portion of δ_n that is not explained by x_n. This error term is assumed to be uncorrelated with x_n. The inequality λ_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 δ_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 β.) 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) $$\underset{N\to\infty}{p\lim}\hat{\beta} = \frac{\underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N}\alpha_n r_n + \underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N}\beta_n r_n y_n + \underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N}\gamma_n' r_n x_n}{\underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N} r_n^2}$$

Making further assumptions that α_n is uncorrelated with r_n, β_n is uncorrelated with $r_n y_n$, and γ_n is uncorrelated with $r_n x_n$, equation (5A) leads to

(6A) $$\underset{N\to\infty}{p\lim}\hat{\beta} = \frac{\underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N}\beta_n r_n^2}{\underset{N\to\infty}{p\lim}\frac{1}{N}\sum_{n=1}^{N} r_n^2}$$

The probability limit of the OLS estimator is then a weighted average of the economy specific β_ns. It is a consistent estimator of that weighted average.[2]

But what if the assumption that every intercept δ_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 λs and ξs and, as a result, the βs and γs are identical across all economies (for the simplicity of the exposition), (3A) can be re-written as

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

[2] 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

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

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 β if *either* $q > 0$ ($y_{nt} - a_t$ is not a first-order AR process) or the cross-sectional variance of ω_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 ω_n can be substantial. This is essentially an omitted variable bias. Evans demonstrates that

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

and

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

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 ω_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 β 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 β and γ. 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.