Scale Effects Found !

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Abstract

A key feature of early endogenous growth models is their prediction of scale effects—the larger the economy, as measured by population, the number of firms, or employment, the faster the economy should grow. However, empirical work has failed to support the existence of scale effects. As a result, much human capital has been expended in order to "fix" this problem by eliminating scale effects in endogenous growth models. We contend that econometric techniques used in the empirical search for scale effects are inconsistent with growth theory. Using data from US states and an econometric technique that better matches growth theory by allowing each economy to have its own steady state, we provide empirical support for the existence of scale effects. Results call into question the need to reformulate the first models of endogenous growth.

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1 Introduction

Since Kaldor (1961), consistency with "stylized facts" has been an overriding theme in the literature on economic growth. The models we build are measured by their concurrence to the perceived stylized facts of growth. The literature on endogenous growth has been successful in explaining several of these patterns (e.g. the massive income gaps that persist between countries). However, the models that were originally developed by Romer (1990), Grossman and Helpman (1991), and Aghion and Howitt (1992) contain an anomolous result that is so constant that it too is now considered to be a stylized fact. Each of these models contains a scale effect in terms of growth rates. They imply that, *ceteris paribus*, larger economies should grow faster than smaller ones. This is due to the relaxed input restraint enjoyed by larger economies. Growth, in these models, is determined by the rate of technological progress which, in turn, is determined by the quantity of resources devoted to the search for new technology. A larger economy has more resources to devote to the development of new ideas, thus, it should grow faster.

The perceived inconsistency of scale effects with the data has led to a second generation of models that eliminate this result. Jones (1995, 2002) develops a model that eliminates the scale effect in terms of growth rates, yet retains a scale effect in terms of income levels. Larger populations are associated with higher income levels.[1] Young (1998), Dinopoulos and Thompson (1998) and others develop models that eliminate scale effects while retaining more of the other salient features of the original endogenous growth models. Specifically, these models retain the policy prescriptions for influencing the growth rate found in the first generation models.

It is fair to say that a great deal of human capital has been spent on the project of de-scaling endogenous growth models. This paper calls into question the need for such a project by resurrecting the empirical search for scale effects in terms of growth rates. We find strong evidence that scale effects in terms of employment are present in the data across U.S. states after controlling for state fixed effects as is suggested by endogenous growth theory. It is often argued that because of the assumed public good nature of ideas the predictions of endogenous growth models are difficult to interpret for any given country or state. We make the case that evidence of persistent

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[1] Similar models are developed in Kortum (1997), and Segerstorm (1998).

technology gaps across the advanced countries as well as the U.S. states make the assumption of a world technological frontier untenable. Borders and geographical distance seem to create more obstacles for the transmission of ideas than is normally granted in the growth literature. In a world of persistent technological gaps across states and countries, political borders make for a natural proving ground for the scale prediction of endogenous growth models.

2 The Case Against Scale Effects

At least since David Hume and Adam Smith independently worked on the question of the ultimate determinant of growth, economists have recognized that technological progress plays a dominant role. Economic analysis as well as simple reasoning also suggest that the profit motive is fundamentally linked with both the speed and direction of technological progress. Even though these ideas have been understood in the literature for many years, they were first incorporated into the formal corpus of economic theory through the work of Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1992) and others. Each of these models that pioneered the analysis of the role played by private incentives and imperfect competition in the determinant of the growth rate of per capita income share the scale effect result. Each model predicts that, in the steady-state, larger economies should grow faster than smaller ones.

The models differ in terms of their microeconomic structure, however, the basic scale effect result can be captured in a simple reduced form model that follows Jones (1995). Suppose that output is produced by the following production function:

$$Y = K^{\alpha}(AL_Y)^{1-\alpha} \tag{1}$$

Where Y is aggregate final output that is competitively produced, K is the capital stock, L_Y is labor used to produce final output, and A is the Harrod neutral level of technology. Given that $\alpha < 1$, the production function exhibits constant returns to scale in terms of capital and labor, and increasing returns in terms of capital, labor, and technology. It is well known and easily shown that the growth rate of per capita income is zero in the steady-state if technology is constant.

This fact leads directly to the need to determine the rate of growth of technology. In these models, technology is made endogenous by assuming that K is an index of non-durable intermediate goods. The number of these intermediate goods provides an index of the level of technology. More intermediate goods represent a more sophisticated production process. Intermediate goods production is assumed to be monopolistically competitive, which is consistent with the need to have a variety of such goods. The production of new technology is assumed to be a function of the amount of labor used to produce new technology (L_A) and the existing level of technology:

$$\dot{A} = \delta L_A^{\lambda} A \tag{2}$$

Where δ indicates the productivity of labor in the production of new ideas that is independent of the level of technology, and is influenced by factors such as the level of human capital available in the economy. The duplication of research effort is allowed for by assuming that $\lambda < 1$. The scale effect is present in equation (2). Divide both sides of (2) by A to generate the growth rate of ideas. The growth rate is positively related to the absolute amount of labor (resources) devoted to the production of new ideas. In the steady-state, L_A/L is constant so that the rate of growth is proportional to the level of employment. Moreover, it can be shown that the steady-state rate of growth in per capita income (γ_y) is equal to the rate of technological progress:

$$\gamma_y = \frac{\dot{A}}{A} = \delta L_A^{\lambda} \tag{3}$$

Thus, in the steady state, scale effects are present in terms of the rate of growth of technology as well as per capita income.

Given the central importance of scale effects to the original endogenous growth models, there has been surprisingly little empirical effort devoted to finding evidence of their existence. Backus, Kehoe and Kehoe (1992) failed to find evidence of scale effects at the national level across a large sample of countries. However, they don't properly control for transition dynamics and other exogenous factors influencing growth not specified by the theory such as the efficiency of government and cultural institutions.

One of the problems in testing endogenous growth models has been the issue of the proper level of aggregation necessary to distinguish a scale type effect. Given the assumption that technology is a pure public good, the world as a whole may be the only true testing ground. This assumption implies that knowledge spillovers are rapid, creating a technology frontier that each state, country, or geographic region is free to exploit. In such a world, scale effects should not be present for any given political unit. Kremer

(1993) shows that the world's population and per capita income historically rose together.

Jones (2002) suggests that the OECD countries may represent the proper level of aggregation given that, by far, most of the world's new ideas are created in these countries. However, most empirical work on the transfer of knowledge suggests that the rate of transfer is slow and dependent on geography and distance. Keller (2002) finds a strong relationship between technology diffusion and geography. He shows that the amount of diffusion is cut in half for each 1200 kilometers from the origin of the technology across 14 OECD countries. Similar results are found in Eaton and Kortum (1996). These results are not particularly surprising given cross-country differences in institutions such as language and educational attainment. More surprisingly, these results are consistent with a slow pattern of technology diffusion across US states and SMSA's. Jaffe, Trajtenberg and Shleifer (1993) find strong evidence that geography is an important determinant of diffusion even after controlling for industry concentration effects. Sedgley and Elmslie (2003) develop evidence on scale effects in patenting statistics that supports this evidence. Zucker, Darby, and Armstrong (1998) also find evidence that knowledge spillovers are geographically limited across US states. Work on the importance of geography in knowledge spillovers has been extended to the MSA level by Anselin et al. (1997) and Varga (2000).

If the diffusion of technology is dependent on geography, each economic unit has a different steady state. Thus far, the literature on scale effects has followed Jones (1995) in assuming that the public good nature of technology makes the scale prediction of the first generation of endogenous growth models difficult to interpret empirically. While the assumption of a global technology frontier is an extremely useful heuristic device, it is not consistent with growth empirics. Technological gaps among the advanced OECD countries are an empirical regularity (Trefler, 1993). Any complete test of the scale effects prediction must account for both transition dynamics and differing steady state growth rates. This paper properly accounts for both. Thus, it represents a complete test for scale effects that is fully consistent with economic theory.

As stated earlier, given the central importance of scale effects to the first generation of endogenous growth models, there has been surprisingly little efforts to test for scale effects empirically. However, this does not mean that evidence consistent with scale effects have not been found. Urban and regional economists have looked at the issue through the lens of agglomeration versus congestion effects. Glaeser et al. (1992) and Glaeser et al. (1995) find a link between population levels and worker productivity across US cities.

In the clearest evidence of scale effects to date, Sedgley and Elmslie (2001) reformulate a traditional endogenous growth model to generate a scale effect in terms of population density. The rate of innovation is shown to be positively related to population density. They test this proposition across US states and find strong empirical support. Moreover, they also test for traditional scale effects at the county and MSA levels. Again, they find strong evidence of the presence of scale effects. Using time-series techniques, Todo and Migamoto (2002) find evidence consistent with traditional scale effects across 17 countries. While the empirical literature on scale effects is limited, there is growing evidence that they may be more a part of the empirical history of growth than is commonly granted by growth theorists.

3 The Empirics of Economic Growth

Derived from Solow (1956) and Swan (1956), the following has become the workhorse of empirical growth research:

$$[\ln(y_{iT}/y_{i,0})/T] = a_i - [(1-e^{-\beta T})/T] \cdot \ln(y_{i0}) + u_{i0,T} \tag{4}$$

where the dependent variable is the average per-capita $\left(y = \frac{Y}{L}\right)$growth rate of economy i over the period between 0 and T and $u_{i0,T}$ is a mean zero, normally distributed disturbance term. The intercept is:

$$a_i = x_i + \left[(1-e^{-\beta T})/T\right] \cdot [\ln(\hat{y}^*)] \tag{5}$$

where x_i is the growth rate of technology and $\ln\left(\hat{y}_i^*\right)$ the steady-state towards which an economy moves at a rate of β. The "hat" notation signifies that the variable is expressed per effective unit of labor$\left(\hat{y} = \frac{Y}{LA}\right)$.

When estimating (4) for a group of relatively homogeneous economies (US states or OECD countries) it is assumed that each economy shares a common pool of technology ($x_i = x$) and approaches a common steady-state $\left(\hat{y}_i^* = \hat{y}^*\right)$. These assumptions allow the removal of the subscript on the entire intercept term such that $a_i = a$ which, after setting $(1-e^{-\beta T})/T = B$, results in the following:

$$[\ln(y_{iT}/y_{i,0})/T] = a + B\ln(y_{i0}) + u_{i0,T} \tag{6}$$

If the assumptions made above hold, then B, called the convergence coefficient, will be negative and significant. Such a result supports convergence–the hypothesis that poor economies will grow faster than rich economies. However, it is well-known that the Solow-Swan model predicts conditional, not absolute, convergence. As such, if the estimate of B is not of the expected sign and significance, our theory tells us that the economies in the sample must differ in terms of their steady state values $\left(\hat{y}_i^{*} \neq \hat{y}^{*}\right)$. In order to account for differences in steady-states, one must include additional independent variables to equation (6) in order to hold the steady state of each economy constant.[2] If the proper variables are chosen, the estimate of B will be negative and significant and we would say that the data supports conditional convergence–the hypothesis that economies will converge not towards the same steady state but towards their own steady state.

For our purposes, equation (6) is important because not only is it used to test the implications of the Solow-type models from which it was derived but it is also used to test endogenous growth models which, in terms of convergence, have completely the opposite predictions. To reconcile this apparent contradiction, recall that endogenous growth models were devised to explain the determinants of growth in the steady state. It is therefore helpful to conceptualize the Solow model as governing the transitional dynamics towards the steady state with endogenous growth models informing us about the position of the steady state itself through the technology parameter A (Pack 1994). As such, the neoclassical and endogenous growth models are not mutually exclusive.[3]

This common approach of assuming a common intercept for all economies and then adding right-hand-side variables to account for differences in the intercepts when the intercepts are indeed different has caused most to overlook a glaring inconsistency with equation (6). Namely, that it attempts to explain growth in per-capita income using a steady-state formulated in terms of growth per effective unit of labor. It is this inconsistency that has precluded a true cross-sectional empirical test of scale effects.

Using the formula for output per unit of effective labor and noting that in the Solow model $A_t = A_0 e^{xt}$:

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[2] Intuitively, adding variables to the right-hand-side of equation (6) 'pulls out' the heterogenity in the intercept term. If all the heterogeneity is accounted for, each economy, in essence, will have the same steady state and thus B should be negative and significant.

[3] See Barro and Sala-i-Martin (1999, pp.41-46) for a formal theoretical model which is consistent with this view.

$$\hat{y} = \frac{Y}{LA} = \frac{Y}{LA_0 e^{xt}} \tag{7}$$

and taking the log of both sides yields:

$$\ln \hat{y} = \ln \frac{Y}{LA} = \ln y - \ln A_0 - xt \tag{8}$$

substituting (8) into (5):

$$a_i = x_i + [(1 - e^{-\beta T})/T] \cdot [(\ln(y^*) - \ln A(0) - xt)] \tag{9}$$

To date, most growth empiricists, whether they are aware of it or not, have followed Mankiw, Romer, and Weil's (1992) "textbook Solow model". M-R-W acknowledge differences in the A_0 term across economies due to economy specific characteristics not only as "technology but resource endowments, climate, institutions, and so on." (p.411) M-R-W then proceed to break the A_0 term into two parts, a common constant (α) and an economy specific component (ϵ) such that $A_0 = \alpha + \epsilon$. They then go to great lengths to explain why they feel ϵ is uncorrelated with the other steady-state components s and n in order to justify lumping it into the error-term and estimating the empirical equation via ordinary least squares (OLS).

While Islam (1995) briefly argues against the validity of OLS, he eventually concludes that the assumption by M-R-W that ϵ is uncorrelated with explanatory variables representing s and n is an "econometric necessity" (p.1134) given the difficulty of the alternative method of estimation (instrumental variable estimation). His "basic conjecture is that a panel data framework provides a better and more natural setting to control for this technology shift term ϵ. (pp. 1134-1135)

Indeed, Islam is correct. A panel data framework, in effect, gives each economy its own steady-state value via an economy-specific time-invariant fixed effect. However, a point that has been overlooked in the literature is that whether OLS is valid or not, if differences in the steady-state as a result of differences in A_0 are not properly accounted for then the empirical estimates that result are not valid tests of the model on which the derived empirical equation is based. And considering the uncertainty surrounding the nature of A_0 it is highly unlikely that any reasonable proxy has been utilized to control for differing steady-states. Although this misspecification certainly casts doubt on the plethora of empirical tests of the speed of convergence, for our purposes it is a display as to why there has never been a true test of the existence of scale effects.

Inserting (9) into (4) and once again setting $(1-e^{-\beta T})/T = B$ produces the new empirical growth equation:

$$[\ln(y_{iT}/y_{i,0})/T] = x_i + B\left[\ln(y^*) - \ln(A_{i,0})\right] - Bxt - B\ln(y_{i0}) + u_{i0,T} \quad (10)$$

Using notation from Islam (1995) the empirical equation based upon (10) is:

$$\begin{aligned} \gamma &= a_i + \eta_t + \beta\ln(y_{i,0}) + \theta\ln E_{i,0} \ + u_{i0,T} \qquad (11) \\ \text{where} : a_i &= B\left[\ln(y^*) - \ln(A_{i,0})\right] \\ \eta_t &= Bxt \\ \ln(y_{i,0}) &= B\ln(y_{i,0}) \\ \ln E_{i,0} &= x_i \end{aligned}$$

Equation (11) is estimated using the method of LSDV (least squares dummy variables) where the use of a_i accounts for any differences in steady-state values across economies which may be due to time-invariant factors in the A_0 term and η_t controls for effects specific to a time period.[4] Consistent with the view of endogenous and neoclassical growth models as presented above, the initial level of per-capita income $(\ln(y_{i,0}))$ is included to control for any transitional dynamics towards the steady-state. We use total employment as our measure of scale.

If one views the two strains of growth theory as mutually exclusive then the convergence dynamics can be removed from equation (10) and the data tested without the initial level of income included. This is the method taken by Backus, Kehoe, and Kehoe (1992). Note, however, that even without convergence, each economy has its own steady-state. This must be accounted for via the specification of different intercept terms as follows:

$$\gamma = a_i + \eta_t + \theta\ln E_{i,t} \qquad (12)$$

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[4] Though it is commonly assumed that the US states are homogeneous in terms of the other variables that determine the steady-state (the savings rate (s), rate of depreciation (δ), and population growth rate (n)) Sedgley and Elmslie (2000) argue that this method of controlling for differing steady-state values, as opposed to the proxy method mentioned earlier, is more accurate because current proxy variables may or may not have any relation to their long-run counterparts.In support, the authors cite the work of Ramsey (1928) in which the Solow model is extended to include consumer optimization. It can be shown that, depending upon the parameters of the model, the savings rate can either rise, fall, or remain constant as the economy approaches the steady-state.

Data from the 48 continental US states is used to test the empirical equation.[5] Panels are constructed for the years 1977-1981, 1982-1986, 1987-1991, 1992-1996, 1997-2000. Growth is measured as the average annual percentage change of GSP per worker over each time-period.[6] The initial level of employment at the beginning of each period is used to avoid endogeneity issues.

A common criticism of dynamic panel data models with fixed effects is that they suffer from biased and inconsistent estimators even if the size of the cross-sectional dimension is quite large (Nickell 1981). Anderson and Hsiao (1981) address this problem by estimating a consistent instrumental variable (IV) estimator via first differences with the first difference of the lagged right-hand-side variable ($y(0)$ in this case) itself instrumented by its second lagged level. While the Anderson-Hsiao method produces consistent estimators for a large time dimension, most panel data models utilize a time dimension that is small. Kiviet (1995) directly estimates a small-sample correction (small in the time dimension) to LSDV estimation. Adam (1998) combines the small-sample bias estimation provided by Kiviet along with the Anderson-Hsiao method to a *STATA* routine that allows a direct application to data. This method, termed $\mathrm{LSDV_c}$, will be employed to for the purposes of discovering the direction of the bias.[7]

4 Empirical Results

Results are presented in Table 1. Regression (1) is the LSDVestimation of equation (11) on the full data set of $N \times T = 240$ observations.[8] Because $\mathrm{LSDV_c}$ requires the use of the first time period (1977-1981) for calculating the correction, we provide LSDV results of the 1982-2000 period (T=4) for comparison as regression (2). Regression (3) is the corrected LSDV regression based upon regression (2). Finally, regression (4) is the estimation of equation (12).

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[5] Data for total employment and GSP comes from the Bureau of Economic Analysis. GSP is in chained 1996 dollars (1996=100).

[6] GSP assigns product to the state in which it is produced whereas personal income is attributed to the state in which the owner of the input resides. Barro and Sala-i-Martin (1992) show that, empirically, results are similar.

[7] Islam (1995) uses an IV estimator based on Chamberlain (1982). Minimum Distance Estimation, as it is called, does not address the potential for small-sample-bias.

[8] Where N=48 states and T=5 time periods.

Table 1–Growth and Employment (1977-2000)

	(1)	(2)	(3)	(4)
$\ln(y_o)$	$-.0568957$ [a] (.017191)	$-.0926825$ [a] (.00238914)	$-.09454966$ [a] (.00238914)	—
$\ln(Employment)$	.0319848 [a] (.0116281)	.0371021 [b] (.017909)	.03721143 [b] (.017909)	.0294798 [a] (.0119083)

Standard errors in parentheses

State and time effects included in each regression but not reported

[a] significant at the .01 level

[b] significant at the.05 level

The scale effect is present and significant in all estimated equations. After accounting for steady-state heterogeneity, states with a larger workforce experience faster productivity growth (growth in per-worker GSP) than those with a smaller workforce. Focusing on the estimated coefficient of scale in regression (1), a 1% increase in employment results in a .032% increase in the growth rate of productivity per year.

Regressions (2) and (3) address the empirical problems associated with dynamic panel equations as described above. Though the results compare with regression (1), the main purpose of performing such a regression on the reduced time dimension panel is to address the direction and significance of the bias. The results demonstrate that the bias is small and in a direction that would only bolster the significance of the scale effect.

Results of regressions (1-3) support the existence of transitional dynamics and the inclusion of $\ln(y_o)$ in our empirical equations. However, even if we assume their absence, as in equation (4), the scale effect is still positive and significant at the .01% level. While the estimated coefficient is not quite the magnitude of regression (1)–and we wouldn't expect it to be given that the transactional dynamics are not being controlled for–such a result demonstrates that the result is robust to either specification.

5 Conclusion

It is routinely proclaimed that if scale effects were present China and India would consistently be the fastest growing economies in the world. Such casual empiricism is so overwhelmingly at odds with a fundamental tenant of the first-generation models of endogenous growth that many have gone to great lengths in order to "save" them. Critiques have been followed by reformulations which have led to critiques of the original critiques and still more reformulations.

It is now generally accepted that all or most (or even a large portion) of the economies of the world are not converging. Large and persistent (and even growing) gaps between rich and poor dominate the empirical record (Pritchett, 1997). Endogenous growth models are better able to explain these undeniable facts than neoclassical models of growth. The problem is not in the models per se, but in the way ideas are modeled. While we agree with the common assumption that knowledge is nonrivalrous (Romer, 1990) we stand with the overwhelming evidence that there are impediments to its flow. Using this idea that knowledge is local in scope, we find strong evidence for the existence of scale effects at the state level.

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