

New Tests of Public Capital's Role in Aggregate Production

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Abstract: This paper presents evidence on the contribution of public capital (infrastructure) to aggregate economic performance using panel data for the U.S. states from 1970 to 2005. Attempts to quantify the role of public or government capital in the production of aggregate output have been beset by thorny econometric issues since the early 1990s. We present estimates of the output elasticity of public capital that are robust to various specifications and assumptions regarding the underlying data generation process.

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1. Introduction

Attempts to quantify the role of public or government capital in the production of aggregate output have been beset by thorny econometric issues since the early 1990s. Around that time, a “rough coincidence”¹ of a slowdown in U.S. public infrastructure investment with a decline in U.S. productivity growth had given rise to a flurry of research that sought to quantify the role of public capital in aggregate production and productivity (Ratner, 1983; Costa, Ellison, and Martin, 1987; Aschauer, 1989, 1997; Munnell, 1990, 1992; Holtz-Eakin and Schwartz, 1995).

One outgrowth of this research was the “public capital hypothesis” – a conjecture that underinvestment in public or government capital was a causal factor in the U.S. productivity slowdown. The issue rose to the top of the nation’s policy agenda in the first Clinton administration. At the time, Mr. Clinton’s first Secretary of Labor, Robert Reich, asserted that public spending on new infrastructure as a percentage of GDP declined from 2.3% in 1963 to 1.0% in 1989.² Such statistics were often cited as part of a campaign to address lagging productivity by rebuilding America’s infrastructure.

The difficulty with substantiating such causal claims, however, stemmed from inconsistent evidence of a link between public capital and aggregate output. Sensitivity of results to choice of functional form (Hulten and Schwab, 1992; Evans and Karras, 1994; Morrison and Schwartz, 1996; Garcia-Mila, T. & McGuire, T. J. &

Porter, 1996), non-stationarity and cointegration (Tatom, 1991), and issues with endogeneity (Eisner, 1991) were at the center of this secondary phase of research activity. In surveying this research and claims associated with the public capital hypothesis, Gramlich concluded that “as for the alleged infrastructure shortfall, the evidence ... is decidedly mixed” (Gramlich, 1994, 1193). Summarizing various estimation issues, Vijverberg, et al were even more skeptical:

“... the issue has not been settled ... it will be hard to ever settle the debate about the effect of public capital on private productivity.” (Vijverberg, et al, 1997, 267.)

In this paper, we provide new econometric evidence in this long-running debate. We begin with what by now has become a conventional estimation strategy: dynamic OLS on panel data, briefly discuss the results and their potential shortcomings, and then move on to newer estimation techniques designed to address the thorny econometric issues alluded to above. When all is said and done, the key insight remains that estimates of output elasticity are surprisingly robust to a variety of functional forms and estimation strategies. Our conclusion is that estimates of the output elasticity of public capital in the range of 0.1 to 0.2 at an aggregate level seem quite reasonable.

2. Preliminary Estimation Results.

The simplest, most straightforward, and most widely used theoretical approach to the question of public capital's role in aggregate output is the aggregate production function, and that is the starting point for the analysis presented here. We analyze the influence of public capital within the framework of a three-input production function, initially following a basic estimation strategy employed in more recent research on the topic:

$$Y_{it} = AN_{it}^{\alpha} K_{it}^{\beta} G_{it}^{\gamma} \quad \alpha, \beta, \gamma > 0, \text{ and } A_{it} = A_0 e^{\delta t}$$

where N_{it} , K_{it} , and G_{it} represent labor, private capital, and public capital inputs respectively in location i at time t , and A_{it} models Hicks neutral technical change.

In logarithmic terms,

$$(1) \quad y_{it} = a_0 + \delta t + \alpha n_{it} + \beta k_{it} + \gamma g_{it}$$

The parameter γ is the output elasticity of public capital. Estimation of this equation would be the most general test of public capital's importance to aggregate economic performance.

Following previous research (Garofalo and Yamarik, 2002), we initially estimate equation (1) using dynamic OLS on a panel of state-level data. The choice of dynamic OLS is motivated by pre-test results that indicated that the variables in (1)

are I(1) in levels, but co-integrated³. Furthermore, and also following previous research, we estimate this equation with two different measures of public capital, g_{it} : the first is a general measure of all state and local public capital stock while the second is a “core” measure that restricts the public capital stock to highways plus water and sanitation facilities.

The cross sections are the 48 contiguous continental states and the time span is 1970 to 2005. As the sample (48 states) is not a random sample drawn from a larger population, fixed effects would seem to be the more appropriate method of estimation.⁴ Previous research, however, has employed both fixed effects and random effects models. A Hausman Test for Correlated Random Effects was inconclusive, thus in Tables 1 we report estimation results from both fixed effects and random effects models. The point estimates of the parameters for labor and private capital sum to 0.948 in the lowest case and 1.061 in the highest case. The null hypothesis of constant returns to scale in private inputs cannot be rejected in any of the four specifications. Furthermore, the magnitudes of the parameters conform fairly closely to the usual assumption of 2/3 payments to labor inputs and 1/3 payments to private capital inputs, although the labor parameters are slightly below this prior expectation. Point estimates of the parameter for output elasticity of public capital range from 0.067 to 0.226. Early estimates of such parameters were criticized for being implausibly large, implying “stratospheric” estimates of the marginal product of public capital (Gramlich, 1994, 1186). The more modest, yet statistically

significant, estimates of the output elasticity of public capital here might be a more realistic picture of public capital's role in the aggregate production process.

One potential shortcoming of such panel estimates is that they impose parameter homogeneity across cross sections. This is a restrictive assumption, and a number of estimation methods have been suggested to consistently estimate linear models with parameter heterogeneity across cross sections. Another issue is the possibility that unobserved common shocks can result in correlated errors across cross sections. The presence of unobserved common factors in linear heterogeneous (heterogeneous slope and factor loadings for cross section units) panel models can also result in between regressors and the error term. If such unobserved common factors are not accounted for, estimation results are likely to be biased as well as inconsistent. Eberherd and Teal (2008), for example, show that presence of cross sectional dependence in heterogeneous panels can significantly distort production function parameters estimates when standard panel estimation techniques are used.

3. Unobserved Common Factors in Heterogeneous Linear Panel Models

To correct for possible distortions, we consider two alternative estimators: the common correlated error mean group estimator (CCEMG) and the augmented mean group estimator (AMG) suggested by Pesaran (2006) and Eberhardt and Bond (2009) respectively. Suppose Y is output and the vector X represents the regressors:

labor, private capital, and public capital. Eberhardt and Bond postulate an empirical model of the form:

$$(2) \quad Y_{it} = \beta' \Delta X_{it} + \mu_{it}$$

$$(3) \quad \mu_{it} = \alpha_i + \lambda_i' f_t + \varepsilon_{it}$$

$$i = 1, \dots, N; t = 1, \dots, T$$

$$\varepsilon_{it} \sim iid$$

X_{it} represents the set of observable regressors, f_t the set of common factors with heterogeneous unit specific effect λ_i . f_t could be stationary or non-stationary. The regressors X_{it} could be modeled as a linear combination of unobserved common factors g_t and f_t . Given (3), $Cov(\mu_{it}, \mu_{jt}) \neq 0$, that is, the error terms are correlated across cross sections. If X_{it} also depends on f_t , $Cov(X_{it}, \mu_{it}) \neq 0$. With only cross-sectional dependence, standard panel estimators are consistent but inefficient, while correlation between regressors and the error term render the estimators inconsistent. Garcia-Mila, McGuire, and Porter (1996) tested for exogeneity in a state panel data covering 1970 to 1983, and found no evidence of correlation between X and μ . Thus we maintain the assumption $Cov(X_{it}, \mu_{it}) = 0$ throughout.

Econometricians have suggested different approaches to estimating β s when cross-sectional dependence is suspected. One approach, suggested by Coakley, Fuertes, and Smith (2002), is to estimate f_t first, and then using estimated f_t in (3). Pesaran (2006), on the other hand, suggests that if the practitioner is only

interested in estimating β' , then to estimate (2) with an augmented model to control for the presence of unobserved common factors, f_t . These proxy variables for f_t are the cross sections mean values of Y and X , and OLS estimates of the mean augmented version of (2) are consistent.

If cross sectional dependence is confirmed, estimation proceeds as follows: if the parameters β are the same across all cross sections (homogeneity case), then estimation using the mean augmented version of (2) with pooled OLS or fixed effects panel seems most appropriate. If, on the other hand, parameters are heterogeneous across cross sections, Pesaran suggests the use of the CCEMG estimator. In heterogeneous models, the mean augmented version of (2) is estimated for each cross section separately, and the consistent estimator of β_i is given by:

$$b_{CCEMG} = N^{-1} \sum_i b_i \quad V(b) = (N - 1)^{-1} \sum_i (b_i - b_{CCEMG})(b_i - b_{CCEMG})'$$

where b_i is estimated by OLS for each cross section. Eberhardt and Bond take the same approach as Pesaran (2006), except they augment (2) with appropriately defined time dummies. The AMG estimator is a two-stage process, where in the first stage, the first differenced version of (2) is estimated by augmenting the right hand side by a set of time dummies. The estimated time parameters are then used in the second stage to account for common effects. Specifically, the models estimated in stage 1 and stage 2 is given by:

$$(4) \quad Y_{it} = \beta' \Delta X_{it} + \sum_t c_t \Delta D_t + \varepsilon_{it} \quad (\text{Stage 1})$$

$$(5) \quad Y_{it} = \alpha_i + \delta_{it} + \beta' X_{it} + d_i u_t^* + \varepsilon_{it} \quad (\text{State 2})$$

where $u_t^* = \hat{c}_t$ estimated from stage 1 regression.

As an alternative, they suggest imposing a unit coefficient on u_t^* , and estimate a modified version of (5):

$$(6) \quad Y_{it} - u_t^* = \alpha_i + \delta_{it} + \beta' X_{it} + \varepsilon_{it}$$

As with the CCEMG estimator, Stage 2 is estimated individually by OLS for each cross-sectional unit, and the AMG estimator is given by, $b_{amg} = N^{-1} \sum_i b_i$. Eberhardt and Bond show that b_{amg} is consistent.

Eberhardt and Bond compare the properties of the CCEMG, AMG, Pooled OLS and Fixed Effect Estimators, the later two augmented with $(T-1)$ first differenced time dummy variables. They report the small sample properties CCEMG, AMG, and Fixed Effect estimators augmented with time dummies under various assumptions regarding the data generating process, and show that the CCEMG and AMG estimators perform better than estimators that ignore the presence of common correlations. They also report that under most data generating processes, the OLS and fixed effect estimators with $(T-1)$ time dummies added as additional regressors

perform as well as the CCEMG and AMG estimator. The data generating process and their implication for estimation are further discussed when estimation results are presented in Section 5 below.

Another issue is whether to estimate the augmented version of (2) in levels or in first differences. If the variables in (2) are either stationary or non-stationary but co-integrated, then estimation in levels is possible. If the variables in (2) are non-stationary and not co-integrated, then estimation in first differences would be appropriate. Therefore, before proceeding to further estimation, we pre-test the data for the presence of common correlations, for stationarity of individual variables, and for co-integration.

4. Common Correlation, Stationarity, and Co-integration

The Pesaran (2004) *CD Test* is used to detect presence of correlation in the error term across different cross section. The applicability of this test along with similar other tests are discussed in Hoyos and Sarafidis (2006). The CD statistic is given by:

$$(7) \quad CD = \sqrt{\left(\frac{2T}{N(N-1)}\right) \sum_{i=1}^{N-1} \sum_{j=i+1}^N \rho_{ij}}$$

where ρ_{ij} are the pairwise correlations between the residuals from the individuals cross-sections,

$$\rho_{ij} = \sum_{t=1}^T (\mu_{it} \mu_{jt}) / (\sum_{t=1}^T \mu_{it}^2)^{1/2} (\sum_{t=1}^T \mu_{jt}^2)^{1/2}$$

The residuals are computed from fixed effect estimation of (2) in levels. The CD statistic is normally distributed. For our data set, the sample statistic = 51.4, which confirms that the error terms of (2) are correlated across cross sections.

Given that the error terms are correlated, the CIPS test suggested by Pesaran (2007) is used to test for non-stationarity in the individual data series. The CIPS test is a mean augmented unit root test assuming a single common factor. For each variable, y , the mean augmented error correction equation,

$$(8) \quad \Delta y_{it} = \alpha_i y_{i(t-1)} + \gamma_1 \Delta y_{i(t-1)} + \gamma_2 \bar{y}_{(t-1)} + \gamma_3 \Delta \bar{y}_t + \gamma_4 \Delta \bar{y}_{(t-1)} + \gamma_5 c_i + \gamma_6 t$$

is estimated by OLS for each cross section i , and the CIPS statistic is given by:

$$CIPS = N^{-1} \sum_i t_i(\alpha_i)$$

Ideally, the lag-lengths in (8) should be chosen by using an information criterion like Akaike or BIC. With a limited number of observations, however, we have estimated (8) with one lag. We note that the error correction equation showed no evidence of serial correlation with lag length limited to one.

The t_i statistic used to construct the CIPS statistic may have to be truncated if too small or too large. Thus, if $t_i < -K_l$ or $t_i > K_h$, use K_l or K_h instead of estimated t_i . Pesaran (2007) provides values for K_l and K_h along with critical values of CIPS test statistic. The unit root test results below indicate that all the variables are I(1) at the 5% level.⁵

<i>Variable</i>	<i>CIPS</i>
Log Output	-2.32
Log Labor	-2.51
Log Priv. Capital	-1.83
Log Pub Capital	-2.53

Since all the variables are I(1), tests for co-integration between Y (output) and X (labor, private capital, and public capital) were performed using the procedure outlined in Gengenbach, Urbain, and Westerlund (2008). This test proceeds the same way as the Pesaran (2007) unit root tests, with the error correction form of (1) augmented with cross sectional mean values of the dependent and independent variables:

$$(9) \Delta y_{it} = \alpha_i y_{i(t-1)} + \beta' X_{i(t-1)} + \gamma_1 \Delta y_{i(t-1)} + \gamma_2 \Delta X_{i(t-1)} + \gamma_3 \bar{y}_{(t-1)} + \gamma_4 \bar{X}_{(t-1)} + \gamma_5 \Delta \bar{y}_t + \gamma_6 \Delta \bar{X}_t + \gamma_7 c_i + \gamma_8 t$$

Once again, we limited the lag lengths to one. The co-integrating equation is estimated individually for each cross section, and the test statistic is the average of the t-statistic for α_i , $\bar{t} = N^{-1} \sum_i t_i(\alpha_i)$. For our sample, we get test statistic of -3.03 (only constant in co-integrating equation) or -3.45 (constant and time trend in co-integrating equation). The critical values are provided by authors, and at the 5% level, and are equal to -3.259 and -3.576 respectively (from Table 3 of Gengenbach, Urbain, and Westerlund, with $m = 3$). This suggests Y, L, Kp, and Kg are not co-integrated.

5. Estimation

Since the unknown common factor could be I(0) or I(1), and with output, labor, private, and public capital I(1) processes that are possibly not co-integrated, estimating (1) in levels is inappropriate. Therefore, the aggregate production function is estimated in first differences. Estimation results, following the approach in Eberhardt and Teal (2008), for the first differenced specification, are in Table 2 and discussed below.

The coefficients for labor and private capital are consistent across all specifications. Whether parameters are allowed to vary across the states in our sample (columns (1),(2), and (4)) or restricted to be same for every cross section (columns (3), (5), (6)), the coefficients of private capital and labor are highly significant, and of similar magnitude. The public capital coefficient is significant in all specifications. In

general, the coefficient of public capital is positive and lies between 0.1 and 0.2, and very similar to the Dynamic OLS estimates presented in Table 1. The results in Table 2 should also be compared to those of Garcia-Mila, McGuire, and Porter (1996) who estimate a first differenced model with state and time fixed effects. The homogenous fixed effect models (columns (3), and (6)), have coefficients for labor and capital very similar in magnitude and significance reported by Garcia-Mila et al. Their model with state and time fixed effect results in capital and labor coefficients of .985 and .348 respectively. We report capital coefficients that are slightly smaller and labor coefficients that are marginally higher. However, there is real divergence with regards to the impact of public capital. For both forms of augmentation for common correlation in fixed effect estimation, public capital is significant with gross output elasticities of .19 and .18 respectively. Garcia-Mila et al, who use a disaggregated series for public capital, report negative but statistically insignificant public capital effect. If we estimate the model, as in Garcia-Mila, McGuire, and Porter, with state and time fixed effects, we get coefficients almost identical to the ones reported in column 6, which in turn are very similar to ones reported in column 3.⁶ This should not be surprising because Eberhardt and Bond show that simple time dummy augmented models do well to proxy for unknown common factors.

These estimates of the public capital coefficient are not too different from those reported by Ramirez (2006) for Mexico, who also used time dummies to augment a

panel data set. Since the CD test points towards common correlated errors, explicitly recognizing them in estimation is important. Both the mean and first-differenced time-augmented models yield a positive co-efficient which are significant across all specifications. Thus, the evidence provided here is sympathetic to that conclusion that public capital has a positive effect on aggregate output.

Eberhardt and Bond have computed the bias in models augmented for the presence for common correlations under various assumptions regarding the data generating process. Of particular interest are the instances where Y and X are not co-integrated, $u_{it} = k(f_{1t}, f_{2t}, \cdot)$, $\mathbf{X}_{it} = g(f_{1t}, f_{3t}, \cdot)$. The common factors f_{1t}, f_{2t}, f_{3t} could be $I(1)$. Thus, there is both common correlations and endogeneity. The authors conclude:

“..the use of ‘naïve estimators’ such as the POLS or Fixed Effects estimators does not create considerable bias in the estimates provided the estimation equation is augmented with $(T-1)$ year dummies.”

Eberhardt and Bond (2009, 7).

Nevertheless, they show that the presence of state specific time trends, two groups of states with common β within group, and feedback effects from Y to X , the mean group estimators are efficient relative to the naïve estimators.

6. Summary

We do not know the exact data generating process behind our data, but we have presented a variety of estimation results with models augmented with either cross-sectional means, time dummies, or an estimate of unknown common factor (u^*), and report a consistent set of results regarding the impact of public capital on output. Since the CD test shows cross sectional dependence, and in light of the results presented by Eberhardt and Bond, we think that the results we have presented are robust.

Obviously, there are certain concerns that need to be addressed in future research. The CD test assumes a single common factor f_t . It is possible to drop this assumption and use a principal components approach. Pesaran, Smith, and Yamagata (2009) have proposed a unit root test with multiple common factors utilizing principal components to identify the number of common factors. Applied to the current problem may yield different results. The co-integration test results show that there is co-integration for about 10 states while the remaining 38 states are not co-integrated. Since the model is estimated in first differences, there is the issue of important long run information being ignored. New developments in the econometrics of panel data involves estimation by imposing homogeneity in long run parameters while allowing heterogeneity in short run parameters across cross sectional units. Estimation imposing long run homogeneity may reveal new information.

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Table 1: Baseline Regressions

Equation (1a): $\ln Y_{it} = a_0 + a_1 t + a_2 \ln N_{it} + a_3 \ln K_{it} + a_4 KG_{it}$
Equation (1b): $\ln Y_{it} = a_0 + a_1 t + a_2 \ln N_{it} + a_3 \ln K_{it} + a_4 KG_{CORE_{it}}$

Estimation Method:	Equation (1a): Total Public Capital Stock		Equation (1b): Core Public Capital Stock	
	Fixed Effects	Random Effects	Fixed Effects	Random Effects
Constant, a_0	0.600 (0.999)	3.926** (0.341)	0.798 (0.910)	4.721** (0.328)
a_1	0.005** (0.001)	0.008** (0.000)	0.005** (0.001)	0.009** (0.001)
a_2	0.561** (0.031)	0.604** (0.029)	0.616** (0.025)	0.659** (0.034)
a_3	0.427** (0.037)	0.344** (0.033)	0.445** (0.042)	0.365** (0.037)
a_4	0.226** (0.043)	0.149** (0.029)	0.173** (0.037)	0.067* (0.027)
<i>F</i> -statistic for $H_0: \alpha + \beta = 1$	0.052	3.237	2.024	0.916
<i>Adjusted R</i> ²	0.997	0.971	0.997	0.970

Notes: Dynamic OLS: Leads and Lags not shown; full estimation results available upon request.
Standard errors are in parentheses.

* Significant at a 5% confidence level.

** Significant at a 1% confidence level.

Table 2: Mean and Time Augmented Estimates of the effect of Public Capital

Parameter	(1) Heterogeneous	(2) Heterogeneous	(3) Common	(4) Heterogeneous	(5) Common	(6) Common
Estimation Procedure	Mean Group	Mean Group	State Fixed Effect	Mean Group	Pooled	State Fixed Effect
Dependent Variable	ΔY	ΔY	ΔY	$\Delta Y - \Delta U^*$	ΔY	ΔY
$\Delta(KP)$	0.289 (0.045)	0.328 (0.033)	0.313 (0.032)	0.291 (0.028)	0.354 (0.029)	0.314 (0.032)
ΔL	0.885 (0.056)	0.957 (0.023)	1.044 (0.036)	.963 (0.025)	.953 (0.033)	1.043 (0.037)
$\Delta(KG)$	0.227 (0.11)	0.181 (0.063)	0.177 (0.067)	0.191 (0.089)	0.116 (0.035)	0.178 (0.068)
Augmented by	Cross Sectional Means, linear time trend	U^* from Equation (3), linear time trend	Cross Sectional Means	Constant, no time trend.	(T-1) First Differenced Time Dummies	(T-1) First Differenced Time Dummies

Notes: (1) Y = Log Output, KP = Log Private Capital, L = Log Labor, KG = Log Public Capital, Heterogeneous = Unrestricted Coefficients across Cross Sections, Common = Common Coefficients across Cross Sections

(2) Ave coefficient of U^* in (2) is .999, linear time trend = 0, no state specific constant.

(3) $\Delta(KP)$ and ΔL are significant at 1% and $\Delta(KG)$ at 5% level of significance for all specifications.

Standard errors are in parentheses.

* Significant at a 5% confidence level.

** Significant at a 1% confidence level.

¹ The term is from Berndt and Hansson (1991).

² See, for example, Reich (1991), 252 – 261.

³ Results available from authors on request.

⁴ On this point, see Baltagi (1995, 68 – 73), Greene (1997, 632 – 633), and Hsiao (1986, 41 – 47).

⁵ The 5% critical value under the null of unit root is equal to -3.87 for $N=50$, $T=30$, and -3.78 for $N=50$, $T=50$

(Pesaran 2007, Table I(c)). In our analysis, $N=48$, $T=36$.

⁶ Results available from authors on request.