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Public health expenditures, taxation, and growth

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Abstract

This note studies the empirical link between public health expenditures and growth using a dynamic panel data model and U.S. state-level data over the period 1963–2015. We find a positive relationship between public health expenditures and growth, even after controlling for the offsetting impacts of the requisite taxation and the government budget constraint.

KEYWORDS

growth, health expenditures, taxation

1 | INTRODUCTION

The literature on the role of human capital for economic growth is extensive. Much of this literature, however, has focused on the growth effects of increased human capital derived through education, with much less attention on the link between health and growth.[1] Bloom, Canning, and Sevilla (2004) point out that better health may be beneficial for growth because healthier individuals are physically and mentally more energetic, less likely to miss work due to ill health, tend to be more productive, and generally receive higher wages. In addition, the fact that healthier individuals generally live longer may have considerable effects on private capital accumulation decisions and therefore on growth (Glomm & Ravikumar, 1997).[2] For these (and other) reasons, national, state, and local governments take leading roles in funding health care. In fact, over the period 1963–2015, annual U.S. state and local government health expenditures averaged about 8% of total state and local general government expenditures. This average, however, is not reflective of the higher average state and local health expenditures over the last decade resulting from the demands of retiring baby boomers on state and local budgets, as well as the passage of the Patient Protection and Affordable Care Act. The Act contained a provision allowing states to expand Medicaid on January 1, 2014. Since then, 36 states and D.C. have adopted the Medicaid expansion.

Recent research has developed theoretical models formalizing a link between health (or health expenditures) and growth (see, e.g., Bloom et al., 2004). This theoretical literature unambiguously shows that health and health expenditures enhance long-run growth. The related empirical evidence, however, is mixed. For example, Wang (2011) finds a positive link between health expenditures and growth, whereas Devarajan, Swaroop, and Zou (1996) report a positive relationship for developed countries but a negative relationship for developing countries.

This note revisits the question of the empirical link between public health expenditures and growth. We make several contributions. First, unlike previous studies that use country-level data, we study the relationship between health expenditures and growth using U.S. state-level data. Cross-country data are known to suffer from measurement error, poor quality, and international and intertemporal data comparability issues. Although the use of state-level data does not eliminate these problems, it significantly ameliorates them. Second, we control for the requisite taxation, the government budget constraint, and other determinants of long-run growth. Third, we address potential joint endogeneity given that

[1]The fiscal decentralization literature has examined the relationship between decentralization and health expenditures or outcomes, with some papers attempting to link decentralization to health outcomes and growth.

[2]Although longer living individuals are likely to be more productive, they generally need increased medical care in retirement, resulting in higher medical costs. This increases pressure on Medicaid expenditures, in particular, given a number of the elderly depend on Medicaid (and Medicare) for a portion or all of medical expenditures.

health expenditures, taxes, and many of the other regressors may be jointly determined with growth. Fourth, we control for time-invariant and time-varying measurement errors by including state-specific effects and lags of the regressors as instruments. We control for joint endogeneity and measurement error by applying the System Generalized Method of Moments (GMM) estimator. This is different from previous papers that employ ordinary least squares (OLS) or fixed and random effects methods. Our results show a positive relationship between state and local health expenditures and growth, whether or not we control for the requisite taxation or the government budget constraint. This finding is, in fact, novel as some studies have argued that in order to identify the growth effects of public expenditures, it is necessary to control for the government budget constraint linking the fiscal variables (see, e.g., Helms, 1985). With state balanced-budget requirements and debt restriction provisions that limit deficit-financing of general fund expenditures, however, the dynamics of state and local fiscal policy are remarkably different than national fiscal policy, validating the (re)assessment of the link between health expenditures and growth using state-level data.

2 | METHODOLOGY

We estimate the model:

$$y_{st} = \beta_1 + \beta_2 y_{s,t-1} + \beta_3 h_{s,t-1} + \boldsymbol{X}'_{i,t-1}\gamma + \delta_t + \eta_s + \varepsilon_{st}, \tag{1}$$

where s refers to states, t to time, η_s to state-specific effects, δ_t to time effects, ε_{st} is the error term, y denotes real per capita gross state product (GSP) growth, h represents state and local health expenditures, and $\boldsymbol{X}'$ is the vector of controls. Depending on the specification, the variables contained in $\boldsymbol{X}'$ include state and local tax revenues (τ), the budget surplus (b), government expenditures net of health expenditures (g), college attainment rate (c), Gini inequality index (ι), union membership density (u), real wage growth ω, the employment-to-population ratio (e), and population density (d). Because our interest is in long-run growth, the variables in the growth models are averaged over 5-year periods in order to net out cyclical fluctuations. h, τ, b, and g are expressed as a share of GSP. The right hand-side variables are lagged by one period, because they are unlikely to contemporaneously impact growth. Table 1 provides summary statistics and data sources of the variables.

The unobserved state effects, η_s are correlated with $y_{s,t-1}$, rendering ordinary least squares (*OLS*) and fixed effects (*FE*) estimators inconsistent. In fact, Arellano and Bover (1995) and Blundell and Bond (1998) show that the *OLS* estimate of the coefficient on $y_{s,t-1}$ will exhibit upward bias, whereas the *FE* estimate will exhibit downward bias. Hence, the estimate of the coefficient on $y_{s,t-1}$ from a consistent candidate estimator is expected to lie between the *OLS* and *FE* estimates. Arellano and Bond (1991) propose the "difference" GMM estimator, which produces consistent estimates for dynamic panel data models such as (1). The estimator first differences (1) to eliminate η_s:

$$\Delta y_{st} = \beta_1 + \beta_2 \Delta y_{s,t-1} + \beta_3 \Delta h_{s,t-1} + \Delta \boldsymbol{X}'_{i,t-1}\gamma + \Delta\delta_t + \Delta\varepsilon_{st} \qquad t = 2, \ldots, T, \tag{2}$$

TABLE 1 Summary Statistics and Data Sources

Variable	Observations	Mean	*SD*	Minimum	Maximum
Real GSP per capita growth (y)	510	0.0218	0.0207	−0.0621	0.1110
Public health expenditure share (h)	510	0.0120	0.0054	0.0027	0.0382
Tax revenue share (τ)	510	0.0841	0.0129	0.0388	0.1211
Budget share(b)	510	0.0083	0.0119	−0.0298	0.1049
Government expenditures net of health expenditures share (g)	510	0.1603	0.0299	0.0626	0.2915
College attainment rate (c)	510	0.1319	0.0599	0.0306	0.4414
Gini inequality index (ι)	510	0.5361	0.0606	0.4282	0.7033
Union membership density (u)	510	0.1700	0.0816	0.0294	0.4158
Real wage growth (ω)	510	0.0156	0.0231	−0.0777	0.0916
Employment-to-population ratio (e)	510	0.5551	0.1125	0.3795	1.3616
Population density (d)	510	325.59	1326.2	0.4112	11632

Note. y, e, d, and ω are from the Bureau of Economic Analysis; h, τ, b, and g from the the Census Bureau; c and ι are from the website of Mark W. Frank ((http://www.shsu.edu/eco_mwf/inequality.html); and u is updated from Hirsch, McPherson, and Vroman (2001) http://unionstats.gsu.edu/MonthlyLaborReviewArticle.htm. Abbreviation: GSP, gross state product.

TABLE 2 Levin, Lin, and Chu (LLC) and Im, Pesaran, and Shin (IPS) panel unit root tests

Variable	LLC Adjusted t^* Statistic	p value	IPS W_{tbar} Statistic	p value
y_{st}	−16.6356	.0000	−7.2163	.0000
h_{st}	− 9.4530	.0000	−1.5904	.0559
τ_{st}	−11.2860	.0000	−3.2790	.0000
b_{st}	−12.5437	.0000	−4.6973	.0005
g_{st}	−12.9676	.0000	−5.5683	.0000
c_{st}	−10.5134	.0000	−3.2274	.0006
ι_{st}	−11.6106	.0000	−5.2128	.0000
u_{st}	− 8.3112	.0000	−2.0414	.0206
ω_{st}	−19.0963	.0000	−7.6900	.0000
e_{st}	−38.2241	.0000	−8.7848	.0000
d_{st}	−9.9922	.0000	−2.0156	.0219

Note. Lag lengths for tests selected by Akaike information criterion.

then exploits the orthogonality conditions:

$$E\left(y_{s,t-q}\Delta\varepsilon_{st}\right) = 0 \quad for \quad t \geq 2 \quad and \quad 2 \leq q \leq T-1 \tag{3}$$

so that second and higher order lags of the levels of y_{st} can be used as instruments.

Lagged levels, however, are known to be poor instruments for first differences (Arellano & Bover, 1995). Further, when y_{st} is persistent, the difference GMM is subject to weak instrument bias. To alleviate these problems, Blundell and Bond (1998) develop the "system" GMM estimator. In addition to estimating (2) using instruments from (3), the system GMM estimates (1) using the moment conditions:

$$E\left(\Delta y_{s,t-1}\left(\eta_s + \varepsilon_{st}\right)\right) = 0 \quad for \quad t \geq 2. \tag{4}$$

Additional moment restrictions may be achieved by using lags of the regressors as instruments. When measurement error is a concern, Blundell and Bond (1998) suggest using longer lags as instruments. Instrument validity is tested using the Hansen J test for overidentifying restrictions. The system GMM assumes that the ε_{st} are serially uncorrelated. We test this assumption using the Arellano and Bond (1991) test for second-order serial correlation. We use the two-step GMM estimator, which is asymptotically efficient and robust to all forms of heteroscedasticity, and apply the Windmeijer (2005) correction to the standard errors.

3 | EMPIRICAL RESULTS

Before estimating (1), we conduct two panel unit root tests, namely, the Levin, Lin, and Chu (LLC, 2002), and the Im, Pesaran, and Shin (IPS, 2003) tests to determine the stationarity properties of the variables. Results of these tests, presented in Table 2, reject their respective unit root null hypotheses, providing some evidence of stationarity of the variables.[3]

Regression (1) of Table 3 estimates the growth effect of public health expenditures when not controlling for other fiscal policy variables. The coefficient is positive and significant, suggesting that public health spending is beneficial for long-run growth. This specification, however, does not control for the government budget constraint or the offsetting impacts of taxation. Regressions (2) and (3) control for taxes and the government budget constraint, respectively. In both specifications, the coefficient on $h_{s,t-1}$ remains significantly positive. In regression (3), a 1-point increase in state and local health expenditures is associated with a 0.13 percentage point increase in long-run growth.

In regressions (1)–(3), the Hansen tests of overidentifying restrictions fail to reject the null hypothesis that the instruments are not correlated with the residuals, validating the joint exogeneity of instruments. As well, the $AR(2)-tests$ do not reject the null hypothesis of no second-order serial correlation in the first-differenced residuals. Furthermore, the system GMM estimate of the coefficient on $y_{s,t-1}(-0.079)$ lies in the credible range—between the OLS (−0.053) and FE (−0.081)

[3]The null (H_0) and alternative (H_a) hypotheses of the LLC are H_0 : *Panels contain unit roots;* H_a : *Panels are stationary.* For the IPS, H_0 :*All panels contain unit roots*; H_a: *Some panels are stationary.*

TABLE 3 Baseline results

Variable	**(1)**	**(2)**	**(3)**	**(*OLS*)**	**(*FE*)**
$y_{s,t-1}$	−0.195***	−0.154***	−0.079***	−0.053	−0.081*
	(0.024)	(0.013)	(0.011)	(0.047)	(0.050)
$h_{s,t-1}$	0.197**	0.203***	0.128***	0.041	0.595*
	(0.090)	(0.066)	(0.048)	(0.170)	(0.392)
$\tau_{s,t-1}$		−0.011			
		(0.074)			
$b_{s,t-1}$			−0.458***	−0.164**	−0.228**
			(0.015)	(0.076)	(0.111)
Time effects	Yes	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes		Yes
AR(2)*test*	**.073**	**.314**	**.176**		
Hansentest	**.048**	**.311**	**.173**		
R^2				0.362	0.345
Number of instruments	37	51	51		
Number of states (and DC)					
Number of observations	459	459	459	459	459

Note. Numbers in parentheses are standard errors, and boldface numbers are *p* values. Instrument set: Third lags of regressors in each regression. Significance at 10%. Significance at 5%. Significance at 1%.

TABLE 4 Robustness checks

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
$y_{s,t-1}$	−0.379***	−0.009	−0.181***	−0.054***	−0.080	−0.022***	−0.205***	−0.196**	−0.261***
	(0.006)	(0.069)	(0.007)	(0.020)	(0.078)	(0.009)	(0.057)	(0.082)	(0.084)
$h_{s,t-1}$	−0.078	0.052	0.008	0.151*	0.099	1.360***	0.512**	0.221	0.378
	(0.077)	(0.069)	(0.114)	(0.085)	(0.223)	(0.029)	(0.212)	(0.193)	(0.392)
$b_{s,t-1}$	−0.373***	−0.150***	−0.217***	−0.305***	−0.449***	0.058***	−1.046***	−0.205**	−0.101
	(0.011)	(0.013)	(0.113)	(0.021)	(0.111)	(0.022)	(0.060)	(0.087)	(0.119)
$g_{s,t-1}$							0.628***	0.138***	0.505***
							(0.042)	(0.035)	(0.080)
$c_{s,t-1}$							0.093*	0.032	0.078
							(0.048)	(0.038)	(0.085)
$\iota_{s,t-1}$							−0.179***	−0.081**	−0.332***
							(0.038)	(0.037)	(0.064)
$u_{s,t-1}$							−0.066***	0.005	0.001
							(0.022)	(0.010)	(0.013)
$\omega_{s,t-1}$							0.330***	0.224**	0.332***
							(0.047)	(0.087)	(0.091)
$e_{s,t-1}$							0.109***	0.002	−0.064
							(0.022)	(0.019)	(0.052)
$d_{s,t-1}$							−0.009***	0.001	−0.005
							(0.002)	(0.001)	(0.008)
Time effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes		Yes
AR(2)*test*	0.017	**.364**	**.092**	**.232**	0.001	**.502**	**.292**		
Hansentest	**.635**	**.532**	**.998**	**.241**	0.000	**.111**	**.756**		
R^2								0.404	0.134
Number of instruments	60	57	84	45	51	42	51		
Number of states	51	51	51	51	51	51	51	51	51
Number of observations	459	459	459	459	459	459	408	408	408

Note. See Table 3. Significance at 10%. Significance at 5%. Significance at 1%.

estimates, giving some degree of confidence in the chosen specification, and bolstering the validity of the finding of a positive relationship between public health expenditures and growth, even when controlling for crowding out effects.

For the discussion that follows, we refer to the specification in column (3) of Table 3 as the baseline specification. To ensure that this specification is credible, Table 4 reports results of several specifications. Column (1) reestimates the baseline specification, but this time uses the first lag of the regressors as instruments; column (2), the second lags;

column (3), the first two lags; and column (4), the fourth lags. In specifications (1)–(3), the coefficients on $y_{s,t-1}$ are not within the *OLS* and *FE* estimates (see Table 3). Furthermore, the number of instruments exceeds the number of groups in all three regressions, potentially causing the *Hansen* test to be weak. The results in column (4), when the instrument matrix is the fourth lags of the regressors, are similar to the baseline results. As well, all specification tests suggest a well-specified model. Column (5) displays results of the one-step variant of the baseline model. Whereas the coefficient on $y_{s,t-1}$ is within the *OLS* and *FE* estimates in Table 3, the *AR*(2) and *Hansen* tests cast doubt on the validity of this specification. In regression (6), we estimate the baseline regression, but this time, without time dummies. Again, the estimate of $y_{s,t-1}$ is not within the *OLS* and *FE* estimates. Model (7) checks for robustness of the baseline results to the inclusion of additional controls. Models (8) and (9) are the OLS and FE estimates of this larger model. In model (7), the estimate of the coefficient on $y_{s,t-1}$ (−0.205) is between the *OLS* (−0.196 in model (8)) and *FE* (−0.261 in (9)). The *AR*(2) and *Hansen* tests, as well, raise no specification concerns. Importantly, the signs and significance of the coefficients on $y_{s,t-1}$, $h_{s,t-1}$, and $b_{s,t-1}$ are similar to the baseline model, suggesting that those results are generally robust to the inclusion of additional variables. Also worth noting is that the estimates of the other variables display the expected signs and are generally in line with previous research (see, e.g., Helms, 1985).

4 | CONCLUSION

This paper estimates the relationship between public health expenditures and long-run growth using data for the 50 U.S. states and D.C. for the period 1963–2015. Our results show that an increase in state and local public health spending is associated with higher long-run growth. This relationship is unchanged even when the crowding out effects of taxation, and the government budget constraint are taken into account. Thus, state and local fiscal policy aimed at increasing the health human capital of citizens can have profound consequences on a state's growth trajectory, a finding consistent with endogenous growth theory, and the empirical literature on the growth effects of productive government expenditures.

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