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ORIGINAL PAPER

Systems GMM estimates of the health care spending and GDP relationship: a note

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Abstract This paper utilizes the systems generalized method of moments (GMM) [Arellano and Bover (1995) J Econometrics 68:29–51; Blundell and Bond (1998) J Econometrics 87:115–143], and panel Granger causality [Hurlin and Venet (2001) Granger Causality tests in panel data models with fixed coefficients. Mime'o, University Paris IX], to investigate the health care spending and gross domestic product (GDP) relationship for organisation for economic co-operation and development countries over the period 1960–2007. The system GMM estimates confirm that the contribution of real GDP to health spending is significant and positive. The panel Granger causality tests imply that a bi-directional causality exists between health spending and GDP. To this end, policies aimed at raising health spending will eventually improve the well-being of the population in the long run.

Keywords Health care spending · Gross domestic product · Systems dynamic generalized method of moments · Panel Granger causality

JEL Classification C1 · I1

Introduction

A considerable body of research within health economics has examined the liaison between health spending and gross domestic product (GDP). Studies such as those by Newhouse [18], Leu [14], Parkin et al. [19], Posnett and Hitiris [20], Hansen and King [9] and Barros [3] highlight that income can have significant effects on health spending. Alternatively, some studies, such as those of Barro [2] and Barro and Sala-i-Martin [4], Knowles and Owen [12, 13], find significant positive evidence on the impact of health spending on economic development.

The link between health spending and GDP is imperative for policy. According to Mushkin [16] and Grossman [8], health can be viewed as an investment in human capital. Since human capital is an engine of growth (Lucas [15], it is inferred that high health spending may result in high levels of output. Scheffler [21] argues that education and health are important for demographic transformation, for instance, as health improves, mortality rate falls. Consequently, an increase in health spending results in higher labour supply and productivity, which eventually raises output growth. For more details see, for example, Erdil and Yetkiner [7] and Muysken et al. [17].

The aim of this article was to examine the association between health spending and GDP for ten organisation for economic co-operation and development (OECD) countries (Austria, Canada, Finland, Iceland, Ireland, Norway, Spain, Switzerland, the United Kingdom and the United States) over the period 1960–2007 using recent methodological advances in panel cointegration and causality testing. We first applied the improved systems generalized method of moments (GMM) dynamic panel data method of Arellano and Bover [1] and Blundell and Bond [5]. Panel Granger causality tests similar to those of Hurlin and Venet [11] were then applied to examine the causal relationship between health spending and GDP.

To the best of our knowledge, Hartwig [10] is the only study that has examined the causality between health and income for OECD countries by applying panel causality tests under system GMM estimates where health is proxied

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by real health care spending. Using annual data over the period 1970–2005, Hartwig find the direction of causality runs from income to health for OECD countries. The present study applies a more recently developed panel Granger causality test (see [11]) to investigate the relationship between health care spending and GDP in the OECD countries using more updated data. In doing so, annual data over the period 1960–2007 were used. A bi-directional causality between health spending and GDP was found to exist; this finding is somewhat different to that of Hartwig [10].

The remainder of the paper is organized as follows: In "Methodology", we briefly discuss the systems GMM [1, 5] and panel Granger causality [11] techniques. "Empirical results" details the empirical results and a "Conclusion" concludes.

Methodology

GMM dynamic panel data method

In what follows, we briefly detail the methodology. The GMM is a semi-parametrically efficient estimation method. The method starts from a set of over-identified population of moment conditions and searches for an estimator that lessens a quadratic norm of the sample moment vector. Consequently, the resulting estimation is reliable and asymptotically normal under appropriate conditions.

Blundell and Bond [5] have shown that GMM first-difference estimators suffer from a major problem. They argue that the instruments used with the standard first-difference GMM estimator become less informative in models where the variance of the fixed effects is particularly high relative to the variance of the transitory shocks. To avoid this bias, Blundell and Bond [5] proposed a system-GMM (henceforth SGMM) estimator that combines in a system the first-differenced with the same equation expressed in levels.

The main advantage of the SGMM method lies in the fact that unlike *within* or *between* (first-differences) methods, it uses the estimation in levels for estimation and this exploits not only the variation in data over time but also between countries (see Arellano and Bover [1] for strengths of SGMM). The latter authors pointed out that SGMM sets an additional sufficient criteria that the correlations between unobserved fixed effects and the explanatory variables are constant over time.

The SGMM method combines the standard set of equations in first differences with suitably lagged levels as instruments with an additional set of equations in levels with suitable lagged first differences as instruments [6]. Thus, the consistency of the GMM estimates depends on the validity of the instruments. The validity of instruments that give a set of over-identifying restrictions has been verified with the standard Hansen test. Furthermore, the Durbin Watson (DW) tests the hypothesis of absence of serial correlation. The standard errors of the estimates are robust to heteroscedasticity.

Panel Granger causality tests

Hurlin and Venet [11] propose Granger noncausality tests for heterogeneous panel data models. We adapt the Granger causality panel data approach with fixed coefficients in which the following two models are examined.

$$\Delta\ln H_{i,t} = \upsilon + \sum_{a=1}^{n} \theta_a \Delta\ln H_{i,t-a} + \sum_{a=0}^{n} k_a \Delta\ln Y_{i,t-a} + u_{i,t} \tag{1}$$

$$\Delta\ln Y_{i,t} = \upsilon + \sum_{a=1}^{n} \theta_a \Delta\ln Y_{i,t-a} + \sum_{a=0}^{n} k_a \Delta\ln H_{i,t-a} + u_{i,t} \tag{2}$$

where ln H is the natural logarithm of real per capita health spending, ln Y is the natural logarithm of real per capita GDP, i is individual of the panel ($i = 1, \ldots, N$), t is time period ($t = 0, \ldots, T$) and n is the maximum number of considered lags. It is assumed that there are balanced panels and identical lag orders (a) for all cross section units. The F tests are utilized to formulate inferences related to Granger non-causality. We test the following hypotheses:

$$\begin{aligned} H_0 &: ki^a = 0 \quad \forall i \in [1,N], \quad \forall a \in [0,n], \\ H_1 &: ki^a \neq 0 \quad \forall i \in [1,N], \quad \forall a \in [0,n], \end{aligned} \tag{3}$$

If the null hypothesis is not rejected, this means that there exists no causality between the variables. According to Hurlin and Venet [11], analysis of causality for panel data sets should consider the different sources of heterogeneity of the data-generating process. For our purpose, we only test the heterogeneous noncausality hypothesis based on the fixed effects model. For details on other tests, see Hurlin and Venet [11] and Erdil and Yetkiner [7].

Empirical results

Panel long run estimates

This section briefly discusses the long run estimates. First, the standard panel data estimates viz., pure cross section or *total* estimates, two fixed effects models viz., *between* and *within* and the random effects model *REM* are reported. Second, we present a single equation estimate with *GMM* in which the first differences of the variables are used. Finally, we use the systems *GMM* approach (*SGMM*). Table 1 reports these results.

Estimates with the country specific time series data and OLS showed that the estimate of β range from 0.362 to 0.713 between these countries. These are not reported to conserve space. We report only estimates with panel data methods in Table 1. These range from 0.745 in column 2 with the fixed effects *between* method to 0.483 in column 5 with the conventional single equation based *GMM* with the first differences of the variables. The rest of the estimates vary from 0.5 to 0.6. The Schwarz Bayesian information criterion (SBIC) selected the estimates with the *REM* in column 4 as the best among these four traditional panel data estimates. For reasons explained in the previous section the *SGMM* estimates in column 6 are to be preferred to single equation based *GMM* estimates in column 5. The *SGMM* estimate of β imply that a 1 % increase in real per capita GDP leads to about 0.669 % increase in per capita real health spending in these OECD countries. Furthermore, the Hansen test confirms that in all cases our set of instruments (the lagged first differences of the variables) is valid. The DW statistic indicates that there exists no serial correlation.

Panel Granger causality tests

We next examined the existence of a causality relationship between H and Y. Lag lengths were selected using Akaike information criterion (AIC). The corresponding lag lengths are one and two, respectively. The panel Granger causality test is based on fixed coefficients; the results are presented in Table 2. Note that, in all cases, the F tests allow us to reject the null hypothesis at the 2 % level. This implies that the existence of a bi-directional causality between per capita health spending and per capita GDP. Our results have some useful implications. Firstly, there is no doubt that these OECD countries are more dependent on human capital and hence it is justified to argue that health Granger causes income. Secondly, in these countries the public share of health spending is substantial. There might be some positive externalities that strengthen the causality from GDP to health spending. Third, these countries were able to successfully adopt policies that focus on raising GDP growth through increasing health spending.

Table 2 Panel Granger causality test results: 1960–2007

Dependent variable	Explanatory variable	F tests
$\ln H$	$\ln Y$	6.560 (0.00)***
$\ln Y$	$\ln H$	5.001 (0.02)**
$\ln H$	$\Delta\ln Y$	10.522 (0.00)***
$\ln Y$	$\Delta\ln H$	5.113 (0.01)***

***, ** Significance at 1 and 5 % levels, respectively. P values in parentheses

Conclusion

In this paper we have used a more efficient SGMM technique to examine the association between health spending and GDP for ten OECD countries. The SGMM based income elasticity of health spending is 0.669. This implies that a 1 % increase in real GDP per capita leads to an increase of about 0.669 % in real per capita health spending in these countries. Next, we used panel Granger causality tests based on a fixed effects model to examine the existence of causality relationships between health spending and GDP. A bi-directional causality was found to exist between per capita health spending and per capita GDP; this finding is somewhat different to that of Hartwig [10]. An implication of this finding is that OECD countries

Table 1 Generalized method of moments (GMM) and system GMM (SGMM) panel estimates 1960–2007

$\ln H_{it} = \alpha_i + \beta_i \ln Y_{it} + \varepsilon_{it}$

	1 Total	2 Between	3 Within	4 REM	5 GMM	6 SGMM
α	0.062 (0.00)***	0.090 (0.00)***	–	0.056 (0.10)	–	−0.031 (0.00)***
β	0.588 (0.01)***	0.745 (0.00)***	0.609 (0.00)***	0.677 (0.00)***	0.483 (0.05)**	0.669 (0.00)***
SER	0.034	0.015	0.018	0.008	0.023	0.014
$\overline{R^2}$	0.562	0.670	0.621	0.754	0.601	1st differences equation = 0.216 Levels equation = 0.702
DW	0.278 (0.00)***	–	0.353 (0.00)***	0.175 (0.00)***	2.456 (1.00)	1st differences equation = 2.563 (1.00) Levels equation 0.056 (0.00)***
ρ_1	–	–	–	0.377 (0.01)***	0.451 (0.00)***	0.380 (0.02)***
ρ_2	–	–	–	0.735 (0.00)***	0.821 (0.00)***	0.411 (0.00)***

DW Durbin–Watson statistic. ρ_1 and ρ_2 are the first and second order serial correlations, respectively. Stata 11.0 was used to perform the tests

***, ** Statistical significance at 1 and 5 % levels, respectively. P values in parenthesis would be successful in raising GDP growth through increased health spending. This may eventually improve the well-being of the population in the long run.

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