The Direction of Causality between Health Spending and GDP: The Case of Pakistan

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THE DIRECTION OF CAUSALITY BETWEEN HEALTH SPENDING AND GDP
The Case of Pakistan

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Abstract. Relevant literature suggests that the most important determinant of health care spending is real *GDP*. Moreover, there is considerable evidence that health care spending rises at a faster rate than real *GDP*. This paper uses recently developed tests for the existence of a long run relationship to analyze the links between health care spending and *GDP*. We are, particularly, interested in estimating the elasticity parameter. The aim of the paper is to provide a new method of analysis to those used in recent papers on this subject. Typically in applied analysis, testing for the existence of cointegration and causality can only be carried out once the time series properties of the data have been established. For example, tests for cointegration require the variables to integrated of the same order, typically I(1), prior to estimation. By eliminating the need for unit root pre-testing, the tests applied here considerably simplify the inference procedure. They also reduce the potential for distortions in the inference due to the unknown properties of the testing sequence. Our findings include robust evidence that, for Pakistan, the income elasticity for health care spending is greater than one and that the elasticity value is stable over the estimation period.

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I. INTRODUCTION

In all developing economies since the 1960s, there has been considerable concern about the increasing proportion of *GDP* devoted to health care spending. As a result, much research has focused on the identification of the factors that contribute to increases in health care spending. The factor that has been identified as the most influential is real *GDP*. In this study, we focus on two issues. The first is an empirical examination of the relationship between real health care spending per capita (*HCS*) and real *GDP* per capita (*GDP*). In this examination, we are interested in the robustness of the relationship between *HCS* and *GDP* over time. The second issue of interest is related to the observation that health care spending may for some economies and for some time periods rise at a faster rate than real *GDP*. If this is the case, the income elasticity of health care spending is greater than one.

There are a number of possible reasons for a positive relationship between the wealth of an economy, as measured by real *GDP*, and the amount spent on health care. First, increased income means that there is more money to spend on health both in the public and private sectors. Second, more health spending may lead to better health status, which may in turn cause higher income. Healthier workers are more productive and hence the economy as well as individuals have more income. This implies that the causal relationship between *HCS* and *GDP* may run in either or both directions. Finally, there may be some associative factor, which causes both better health and higher income. An example would be increased education levels in an economy which increase demand for *HCS* and independently, increase income.

The rest of the paper is organized as follows: A brief study of previous empirical studies is presented in section II. Section III provides data and methodology. Robust empirical findings are discussed in section IV and the main conclusions are stated in section V.

II. REVIEW OF RELEVANT LITERATURE

Until recently much of the focus of applied analysis on the relationship between *GDP* and *HCS* has been on results from pooled cross section data from the OECD countries (see for example, Gerdtham, Søgaard, Andersson and Jönsson, 1992). Recent work has, however, cast some doubt on the validity of the pooling restrictions. Blomqvist and Carter (1997, p. 226) after an extensive econometric analysis of the data in an attempt to estimate the income elasticity of demand for health, conclude by noting that “pooling restrictions are of very doubtful validity.” Further questions on the validity of pooling the data come from three recent papers, which analyze the time series properties of the data. Hansen and King (1996) use standard Augmented Dickey-Fuller (ADF) tests for unit roots and Engle Granger tests for cointegration using OECD data on *HCS*, *GDP* and a variety of other variables thought to influence health care spending. They find that the time series properties of the data varies between countries. Thus, for example, their results suggest that *HCS* in Pakistan is I(0), in France it is I(1) and in Norway it is I(2). Using individual country analysis they find little evidence of cointegration between the variables, casting doubt on previous empirical work which used OLS estimation. If we take these results at face value then they clearly confirm Blomqvist and Carter's conclusion that it makes no sense to pool data where the basic time series properties of the data are of such different orders of integration.[1]

In a related paper, McCoskey and Selden (1998) use recently developed tests for a unit root in a panel setting. The test they use, that of Im, Pesaran and Shin (1997), takes advantage of increased power due to the pooling of the data but has the advantage of allowing a degree of heterogeneity in the data generating process of the individual elements of the panel. This last point needs further consideration. When testing for unit roots, two key decisions need to be made. The first is what deterministic variables to include in the regression model in which the unit root null is to be tested. This decision depends in part on the assumption made about the unknown data generating process. For example, an assumption is made about whether the variable is a random walk or random walk with drift for example. An incorrect decision can lead to a loss of power and the possibility that the test statistic will not have the tabulated Dickey Fuller distribution. The second decision concerns lag orders in the ADF to ensure that the residuals of the test regression are not auto-correlated, again some decision must be made from observation of the diagnostics of the test regression. This is the heterogeneity that the Im, Pesaran and Shin (1997) test makes allowance for. Each series can be tested using a different set of deterministic variables and differing lag order in the ADF and this is a significant improvement over previous tests. The problem is, as pointed out in Hansen and King's (1998) comment to the paper by McCoskey and Selden (1998), that the null hypothesis in the panel based unit root test is that all of the series in question

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[1]The most recent developments in the analysis of panel data may provide solutions to these problems, *see*, for example, Banerjee (1999).

are I(1) whilst the alternative is that they are all I(0). Clearly it is possible, as Hansen and King (1998) point out that such tests could lead to the rejection of the unit root null even when it was the case that some of the individual series could not reject the unit root null. Clearly this is an important issue. The test is not applicable in cases where the heterogeneity stretches to series with differing orders of integration.

Roberts (1999) in her summary of the papers mentioned above, identifies three weaknesses in the estimation procedures which have been used to explore the relationship between *GDP* and *HCS*. First, the use of cross sectional data imposes homogeneity on the institutional characteristics of countries used in the sample, whereas there are considerable differences between the way health care is funded and organized in different economies. The second weakness is the failure of much modeling to take into account the dynamics in the relationship though the use of an appropriate lag structure. The third weakness is the difficulty of dealing with variables that are non-stationary. We account for all these weaknesses in our analysis.

We believe that the above discussion validates our decision to analyze the data from an individual country, time series perspective. Clearly this involves a loss of power compared to the panel based approach, but we believe that the problem of the possible heterogeneity of the panels justifies our approach. Weighed against this is the fact that our testing procedures obviate the need for pre-testing the variables for unit roots. Typically in applied analysis, testing for the existence of cointegration and causality can only be carried out once the time series properties of the data have been established. For example, tests for cointegration require the variables to be integrated of the same order, typically I(1), prior to estimation. Similarly tests for causality are influenced by the need to know about the unit root and cointegration properties of the data. By eliminating the need for unit root pre-testing, the tests applied here considerably simplify the inference procedure. They also reduce the potential for distortions in the inference due to the unknown properties of the testing sequence.

III. METHODOLOGY AND DATA

This paper uses recently developed tests for the existence of a long run relationship to analyze the links between *HCS* and *GDP* using Pakistan's time series data taken from the *Pakistan Economic Survey* and *Annual Reports* (various issues). This data series is annual from 1972 to 2005 and thus comprises 33 years of observations.

ESTIMATION TECHNIQUES

The first test applied to the data is the one suggested in Pesaran, Shin and Smith (1999). This tests for a long run relationship between the variables and is applicable irrespective of whether the regressors are I(0), I(1) or mutually cointegrated. The test is based upon estimation of the underlying VAR model, re-parameterized as an ECM (error correction model).[2]

The VAR(p) model:

$$z_t = b + ct + \sum_{i=1}^{p} \Phi_i z_{t-i} + \varepsilon_t \tag{3.1}$$

where z represents a vector of variables. Under the assumption that the individual elements of z are at the most I(1), or do not have explosive roots, equation (3.1) can be written as a simple Vector ECM.

$$\Delta z_t = b + ct + \Pi z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta z_{t-i} + \varepsilon_t \tag{3.2}$$

where $\Pi = -\left(I_{k+1} - \sum_{i=1}^{p} \Phi_i\right)$ and $\Gamma_i = -\sum_{j=i+1}^{p} \Phi_j, i = 1, ... p-1$ are the $(k+1) \times (k+1)$ matrices of the long run multipliers and the short run dynamic coefficients. By making the assumption that there is only one long run relationship amongst the variables, Pesaran *et al.* focus on the first equation in (3.2) and partition z_t into a dependant variable y_t and a set of forcing variables x. This is one of the key assumptions of their paper. Under such conditions the matrices b, c, Γ and, most importantly, Π, the long run multiplier matrix can also be partitioned conformably with the partitioning of z.

$$\Pi = \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \Pi_{22} \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \quad c = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} \quad \Gamma_i = \begin{bmatrix} \gamma_{11,i} & \gamma_{12,i} \\ \gamma_{21,i} & \gamma_{22,i} \end{bmatrix}$$

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[2]Most of the following is based on Pesaran, Shin and Smith (1999) and follows their original notation.

The key assumption, that x is long run forcing for y, then implies that the vector $\pi_{21} = 0$, that is that there is no feedback from the level of y on Δx. As a result the conditional model for Δy and Δx can be written as

$$\Delta y_t = b_1 + c_1 t + \pi_{11} y_{t-1} + \pi_{12} x_{t-1} + \sum_{i=1}^{p-1} \gamma_{11,i} \Delta y_{t-i} + \sum_{i=0}^{p-1} \boldsymbol{\gamma}_{12,i} \boldsymbol{\Delta x}_{t-i} + \varepsilon_{1t} \tag{3.3}$$

$$\Delta x_t = b_2 + c_2 t + \boldsymbol{\Pi}_{22} x_{t-1} + \sum_{i=1}^{p-1} \gamma_{21,i} \Delta y_{t-i} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_{22,i} \boldsymbol{\Delta x}_{t-i} + \boldsymbol{\varepsilon}_{2t} \tag{3.4}$$

Under standard assumptions about the error terms in (3.3) and (3.4)[3] Pesaran *et al.* re-write (3.3) as

$$\Delta y_t = a_0 + a_1 t + \phi\, y_{t-1} + \delta\, x_{t-1} + \sum_{i=1}^{p-1} \upsilon_i \Delta y_{t-i} + \sum_{i=0}^{p-1} \varphi_i \Delta x_{t-i} + \varpi_t \tag{3.5}$$

which they term an unrestricted error correction model. Note that in (3.5) a long run relationship will exist amongst the levels variables if the two parameters ϕ and δ are both non zero in which case, for the long run solution of (3.5) we obtain

$$y_t = -\frac{a_0}{\phi} - \frac{a_1}{\phi} - \frac{\delta}{\phi} x_t \tag{3.6}$$

Pesaran *et al.* choose to test the hypothesis of no long run relationship between y and x by testing the joint hypothesis that $\phi = \delta = 0$ in the context of equation (3.5). The test they develop is a bounds type test, with a lower bound calculated on the basis that the variables in x are I(0) and an upper bound on the basis that they are I(1). Pesaran *et al.* (1999) provide critical values for this bounds test from an extensive set of stochastic simulations under differing assumptions regarding the appropriate inclusion of deterministic variables in the ECM. If the calculated test statistic (which is a standard F test for testing the null that the coefficients on the lagged levels terms are jointly equal to zero) lies above the upper bound, the result is conclusive and implies that a long run relationship does exist between the

[3] Essentially that they are independently normally distributed with a positive definite variance covariance matrix.

variables. If the test statistic lies within the bounds, no conclusion can be drawn without knowledge of the time series properties of the variables. In this case, standard methods of testing would have to be applied. If the test statistic lies below the lower bound, no long run relationship exists.

EMPIRICAL FINDINGS

In the context of the above discussion a key element of the testing strategy is the assumption that the variables contained in *x* are long run forcing for *y*. Clearly in many applications, such information is not available *a priori*. To counter this problem, Pesaran *et al.* advance a testing strategy which assumes no particular ordering of the variables into *x* and *y* vectors and requires estimation of the ECM in all of its inversions. Whilst it may seem reasonable to assume that HCS is not a long run determinant of *GDP* and hence that estimation and testing could take place in a regression of the form below in equation (3.7), we do estimate the model with both ΔGDP and ΔHCS as the dependant variable. Our prior is that if there is a long run relationship between the two variables the F test will be significant when ΔHCS is the dependant variable and not significant when ΔGDP is the dependant variable. This would indicate that *GDP* is long run forcing for *HCS* but not *vice versa*.

Two further aspects of the regression equation need specifying in practice. First we specify the lag order, *k* in the regression. We started testing with a maximum lag of 2 and used information criteria and sequential F tests along with tests for residual autocorrelation to guide our lag choice. Since this is annual data and we wish to preserve as many degrees of freedom as possible, this seems a reasonable maximum lag order. The second decision regards the inclusion of deterministic constant and trend terms. We report here tests based on a model with an unrestricted constant, since we found no evidence of a significant deterministic trend in the relationship. We based our decision on lag order on the observation of both the information criteria, an F test of the reduction (from 2 lags to 1 lag) and the autocorrelation test.

$$\begin{aligned}\Delta HCS_t &= \alpha_0 + \alpha_1 HCS_{t-1} + \alpha_2 GDP_{t-1} \\ &\quad + \sum_{i=1}^{k}\gamma_i \Delta HCS_{t-i} + \sum_{i=0}^{k}\delta_i \Delta GDP_{t-i}\end{aligned} \tag{3.7}$$

Tests of the null hypothesis of no long run relationship can thus be carried out using an F test of the null that $\alpha_1 = \alpha_2 = 0$.

TABLE 1

Results for estimation of Equation 3.1 with lag orders k = 1,2

Constant only, Dependant variable ΔHCS

Lag order	SC	HQ	LM AR(1-2)	F test on Reduction
$K = 2$	–6.352	–6.585	[.02]*	
$K = 1$	–6.545	–6.720	[.58]	[.87]

Constant only, Dependant variable ΔGDP

Lag order	SC	HQ	LM AR(1-2)	F test on Reduction
$K = 2$	–6.998	–7.231	[.31]	
$K = 1$	–7.190	–7.365	[.66]	[.86]

NOTE: Figures in square brackets are p values.

From the results in Table 1, lag order, $k = 1$, seems appropriate as both information criteria select $k = 1$, the F test does not reject the reduction in lag order from 2 to 1 and there is no evidence of serial correlation in the residuals. Table 2 shows the F tests for the restrictions that the lagged terms are jointly zero. When ΔHCS is the dependant variable, we reject the null of no long run relationship between the variables, but do not reject it when ΔGDP is the dependant variable, implying that a long run relationship does exist and that it is *GDP* that is long run forcing for *HCS*.

TABLE 2

F Test for the Existence of a Long Run Relationship
Constant only

Dependant variable	F statistic
ΔHCS	6.53
ΔGDP	3.04

NOTE: 95% critical bounds for the F test: 4.94 – 5.73[4]

[4]Critical bounds are from Table C1.iii of Pesaran *et al*. (1999).

The estimated regression, with ΔHCS as the dependant variable for the sample period 1972 to 2005 is:

$$HCS = \underset{[0.5782]}{-2.043} + \underset{[0.1826]}{0.1636}\,\Delta HCS_{t-1} + \underset{[0.2162]}{0.1351}\,\Delta GDP$$

$$\underset{[0.2807]}{-0.2143}\,\Delta GDP_{t-1} + \underset{[0.1511]}{0.5488}\,GDP_{t-1} - \underset{[0.08439]}{0.3122}\,HCS_{t-1}$$

$R^2 = 0.42473$, F = 4.2822 [0.0049], DW = 1.97

Since the evidence suggests there is a long run relationship between *HCS* and *GDP*, we estimated the long run relationship using the autoregressive distributed lag (ARDL) method suggested in Pesaran, Shin and Smith (1999).[5] A maximum lag order of 3 was allowed in the ARDL model and we used the Schwarz Bayesian Criteria to select optimal lag orders. In this case, an ARDL (1,0) model was selected and the estimated long run relationship was of the form:

$$\begin{array}{lll} HCS = & -6.53 & + \; 1.76\,GDP \\ se & (0.760) & (0.140) \\ t & (-8.06) & (12.59) \end{array}$$

The coefficient on GDP is highly significant. It is also of interest that the 99% confidence interval around the estimated coefficient does not include 1, implying that the elasticity of demand for health care in Pakistan is greater than 1 and thus implies that people can spend more on this because it is a necessity good. This finding is consistent with the results in Blomqvist and Carter (1997). Furthermore, we find evidence that there is a long run relationship between *GDP* and *HCS* and direction of the relationship runs from *GDP* to *HCS*.

[5]This method is, once again, applicable irrespective of whether the regressors are I(0) or I(1). The long run estimates and their standard errors were obtained using Microfit 4.0. (Refer to Pesaran and Pesaran, 1997). This uses Bewley's (1979) regression method to estimate the asymptotic standard errors and is equivalent to the so-called 'delta' method (*see*, for example, Greene, 1993, p. 297). Monte Carlo experiments in Pesaran and Shin (1999) suggest that the ARDL approach may well be preferable to other estimators such as Fully Modified OLS (Phillips and Hansen, 1990) in small samples.

IV. THE ROBUSTNESS OF THE RESULTS

Whilst the key element of our testing procedure so far is to test for the existence of a long run relationship without the need to pre-test for unit roots it does seem prudent to carry out further, more standard tests, to establish the robustness of the above results. Since the above tests do depend on a number of assumptions, such as the weak exogeneity status of *GDP* and the assumption that the maximum order of integration is I(1), we re-examine the relationship using the Johansen maximum likelihood method of testing for cointegration. We bear in mind throughout that whilst the span of our data is good we are carrying out these tests with a smaller number of observations than is desirable. Against this we note that the results below prove to be so close to those obtained above that we believe they serve to strengthen our conviction in the numbers produced.

The standard ADF tests for a unit root in the log levels and first differences of the data both confirm the assumption that *HCS* and *GDP* are both I(1). On the basis of this confirmation, we proceed to the Johansen estimation. Before carrying out the estimation, we need to establish a valid lag order in the levels of VARS of the variables.

Once again, because the data are annual and the degrees of freedom are small, we estimated a VAR with the variables expressed in levels, and including a constant and a maximum of two lags of *HCS* and *GDP*. A simple model reduction using a VAR reduction sequence suggests that a VAR(1) is in fact adequate and has acceptable diagnostics.

TABLE 3

Johansen's Test for Cointegration

No. of cointegrating vectors	Max. Eigen value Statistic	Adjusted Statistic	5% critical value	Trace test statistic	Adjusted statistic	5% critical value
= 0	19.02*	17.99*	14.1	22.51*	21.29*	15.4
≤ 1	3.488	3.3	3.8	3.488	3.3	3.8

NOTE: Estimation sample 1972 to 2005, constant entered unrestricted, no trend.

Table 3 reports the results of the Johansen maximum likelihood method of testing for cointegration. The results suggest that there is a single cointegrating vector between variables. The constant enters the estimation unrestricted to allow for possible non-zero drift in the series. The estimated cointegrating relationship yielded a coefficient on *GDP* (when normalized) of 1.695 implying a long run elasticity in accordance with that obtained using the ARDL approach. One advantage of the Johansen method at this stage is its ability to test restrictions on the cointegrating vector. Under the assumption that the rank of $\alpha\beta = \Pi$ (the long run matrix) is unity we carry out two types of tests. First, we restrict the β matrix so that only one of the variables entered the cointegrating relationship. For example, we restrict the coefficient on *HCS* to be zero and that on *GDP* to be arbitrarily one. This tests the null that the unrestricted variable is I(0) (cointegration with a single variable). This is often referred to as the multivariate test for stationarity. Table 4 reports the results. The strong rejections of the null support the results of the ADF tests that the variables are both I(1). Second, by appropriate restrictions on the α matrix we can test the weak exogeneity assumption important in the ARDL test. Once again these tests suggest that we cannot reject the hypothesis that the cointegrating relationship only enters in the *HCS* equation of the system, supporting the notion that *GDP* is weakly exogenous and that the restriction assumed above in the ARDL testing is valid.

TABLE 4

Tests for a Unit Root and Weak Exogeneity

	LR test ($\chi^2(1)$)
Unit root for *GDP*	12.84 [.00]
Unit root for *HCS*	10.65 [.00]
Weak exogeneity *GDP*	0.92 [.34]
Weak exogeneity *HCS*	14.97 [.00]

Both sets of tests show evidence of a long run or cointegrating relationship between the two variables of interest. The fact that both of the tests produce similar estimates of the income elasticity adds weight to our conclusion that in Pakistan, people spend more on health care because it is a necessity good.

Whilst we have estimated parameters for the long run relationship we have not, at this stage tested for their stability, in order to do so we used the tests described in Hansen (1992). Hansen details three tests of parameter instability in the context of a regression involving I(1) variables, these are the SupF, MeanF and L_C tests. Hansen shows that the latter test can be used as a test of the null of cointegration, thus providing us with a further check of the cointegration result obtained above. In order to implement these tests we use the GAUSS program along with a program written specifically to carry out the tests mentioned above by Hansen.[6] The method also requires the use of the FM-OLS type estimators of cointegrating relationships suggested by Phillips and Hansen (1990), providing a further check on the results above.

Firstly, the FM-OLS results were:

$$\underset{}{HCS_t} = \underset{(0.06)}{-6.76} + \underset{(0.32)}{1.78}\, GDP_t$$

Once again these results are very close to the estimates obtained from the other methods. None of the three parameter stability tests reject the null hypothesis of stability. The L_C test fails to reject the null of cointegration, once again supporting the idea of a long run relationship between the two variables.

Finally, since all of the above appears to confirm the existence of a long run relationship, we use the estimated regression to form an error correction term and estimate a simple dynamic ECM for health care spending. The estimated regression is reproduced below with a standard range of diagnostics. Since all of the regressors are I(0), either due to first differencing or construction (in the case of the ECM), Hansen's (1992) tests for parameter stability are applicable. These show no evidence of instability in either individual parameters or the regression as a whole.

TABLE 5

Error Correction Model for *HCS*

Variable	Coefficient	Std. Error	t-value	Instab
Constant	–0.0042558	0.010498	–0.405	0.07
ΔHCS_{t-1}	0.16366	0.14345	1.141	0.09
ΔGDP_t	0.13580	0.22960	0.591	0.21
ΔGDP_{t-1}	–0.21430	0.27813	–0.771	0.06
ECM_{t-1}	–0.31246	0.085008	–3.676	0.10

R^2 = 0.424729, F (4,30) = 5.5373 [0.0018], DW = 1.97

[6]The program is available from Prof. Hansen's home page at: http://www.ssc.wisc.edu/~bhansen/

The error correction term is correctly signed and significant. The value of the coefficient on the ECM indicates that a change in real *GDP* brings about a 31% change in *HCS* in a year. Alternatively, it takes approximately 3 years for any deviation from the long run relationship between *HCS* and *GDP* to be corrected after a change in GDP. The ECM also passes a range of diagnostic tests.

V. CONCLUSIONS

Our results support the hypothesis that over the period 1972 to 2005, *HCS* in Pakistan rose at a faster rate than *GDP*. The value and sign of the income elasticity on health care spending is confirmed by three different test procedures. Importantly, our results in section 4 of the paper support the size and sign on the elasticity over the entire sample period. We also find strong support for the exogeneity of *GDP* and the existence of a long run relationship between *GDP* and *HCS*. The ECM for the relationship between *HCS* and *GDP* supports a three year adjustment period to equilibrium after a change in *GDP*.

Our analysis of the relationship confronts all three criticisms made by Roberts (1999). Rather than make the questionable assumptions involved in aggregation into panels we chose to analyze the relationship between *GDP* and *HCS* on a single country basis, using Pakistan as our first subject. Further, we consider the dynamics of the relationship between *HCS* and GDP by a careful consideration of the appropriate lag structure at all stages of our analysis. Finally, our techniques consider the stationarity of the variables.

Given the nature of the available data, drawing inferences about the determinants of health spending is a process fraught with difficulty. The main difficulty we have faced is with the number of observations available. In order to alleviate the data problems as much as possible we use a recently developed test for the existence of a long run relationship between time series which conserves degrees of freedom in pre-tests for unit root characteristics of the data. We also acknowledge that there are limitations in the quality of the data. In particular, gross domestic product is an imperfect indicator of economic prosperity and not all improvements in health status can be attributed to changes in health care spending. Nonetheless, the size of the income elasticity on *HCS* confirms the widely accepted view that over the last 30 years, *HCS* has tended to grow at a faster rate than *GDP* in Pakistan.

Our results confirm the long held view that the most important factor that influences changes in *HCS* in an economy is changes in *GDP*. As a country grows, it has more resources to devote to the health care sector. We do not anticipate, however, that the relationship between *HCS* and *GDP* which we have described is likely to hold for future time periods. The period between 1972 and 2005 witnessed enormous advancements in medical technology, increasing community expectations and population aging. Most importantly, it was also a period when governments were more amenable to increases in the health budget and a large proportion of the health spending in Pakistan is public. There is a greater acceptance now that health resources should be rationed and that public health spending cannot continue to grow as it did over the period under review. An avenue for further research is the application of the techniques which we have used in this paper to the relationship between *HCS* and *GDP* in different countries and also to future time periods for the Pakistan's economy.

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