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Do Fluctuations in Health Expenditure Affect Economic Growth?

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Abstract: The temporal interdependence between health expenditure and economic growth has been the focus in a number of recent empirical studies. While some insights have been gained from these studies, the focus has been on national economies, either in developed or developing countries. This paper explores this relationship at the U.S. state-level. The paper contributes to the literature by investigating possible dynamic relations between health care expenditure and economic growth, measured by gross state product, in the southeast United States. By employing time series approach, the empirical results confirm the presence of a weak, but positive relationship. After detecting unit roots in the data, cointegration in general, was not detected, as a long-run relationship seemed to exist only for Georgia. The results of the VAR analysis are correspondingly limited. However the shapes of the impulse functions do confirm the proper positive relationship between positive personal health care expenditure changes and economic growth.

Keywords: Personal health care expenditure, economic growth, gross state product, time series.

I. INTRODUCTION

The relationship between health spending and economic growth is well established in the literature, yet the direction of causation of this relationship remains contentious (Kleiman) [1], Newhouse [2], Hansen and King [3], Blomqvist and Carter [4], McCoskey and Selden [5], Gerdtham and Lothgren [6], Karatzas [7], Bloom, Canning and Sevilla [8], Arora [9], Bhat and Jain [10]). In a seminal paper, Newhouse ([2], pp. 115-25) examined this relationship and confirmed earlier findings by Kleiman [1], suggesting that a country's per capita GDP is the single most important factor influencing health spending. This finding shaped the foundation for a large body of literature, which view income as a major determinant of health care expenditure (Behrman [11], pp. 54-8, Barro and Sala-i-Martin [12], Bloom and Sachs [13]). To the contrary, several studies have argued that health does not play an important role in influencing productivity, concluding instead that health is not an important variable when it comes to explaining economic growth (Cullis and West [14], p. 84-89, Easterly and Rebelo [15], p. 417-58, Acemoglu and Johnson [16]).

Amidst the mixed evidence, recent studies (Gallup and Sachs [17], Getzen [18], Reinhardt, Hussey and Anderson [19]) have employed modern analytical techniques and have produced new results that suggest a feedback effect between health spending and GDP per capita. If the causal relationship runs in both directions, the ordinary estimations used in earlier studies would yield biased and inconsistent estimates of the structural parameters (Rivera and Currais [20]); thus calling for different empirical techniques for understanding the relationship between these two variables. The aim in this paper therefore, is to investigate possible dynamic relations between personal health care expenditure (PHCE) and economic growth (GSP) using univariate and multivariate time series analysis. While most studies in the literature have focused on national economies, either in developed or developing countries, the current analysis explores this relationship at the U.S. state-level.

The remainder of the paper is organized as follows: Section 2 presents a review of studies linking health and economic growth; Section 3 presents the data followed by the methodological approaches, and the results in Sections 4 through 7. Stationarity tests are first performed in Section 4 to assess likely trends. Cointegration analysis follows in Section 5, to analyze the stationary relationship between these variables. Section 6 examines the interrelationship between personal health care expenditure and gross state product using causality test. To explain the dynamics of the interrelationship between personal health care expenditure and economic growth, vector autoregressions have been estimated in Section 7, and impulse functions are computed to measure possible delays between variable reactions. The final section contains the concluding remarks.

II. HEALTH AND ECONOMIC GROWTH

An insightful review of the literature on the nature of links between health and productivity (GDP) has been provided by Bhat and Jain [10], Bloom and Canning [21], Lo'pez-Casasnovas, Rivera and Currais [22] and recently by Finlay [23]. While Bhat and Jain [10] summarize the literature in several broad categories based on methodological techniques, Bloom and Canning [21] and Lo'pez-Casasnovas, Rivera and Currais [22] approach the literature from a micro and macroeconomic perspective; whereas Finlay [23] breaks the literature into empirical and theoretical studies.

On a microeconomic level, different health indicators have been used in the literature based on the idea that healthier workers are less susceptible to disease, more alert, more

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energetic, and consequently more productive and command higher earnings (Bloom and Canning [21], Lo´pez-Casasnovas, Rivera and Currais [22]). Notable studies include Grossman [24], Muurinen [25], Forster [26], Ehrlich and Chuma [27], Johansson and Lofgren [28] and Meltzer [29]). As Lo´pez-Casasnovas, Rivera and Currais [22] have noted, the main problems with these kinds of analyses is that they typically suffer from measurement errors when it comes to capturing the individual's health status, heterogeneity of the variables, and the possible feedback among them.

Macroeconomic studies are based on a model in which economic growth during an interval of time is a function of initial income, economic policy variables, and other structural characteristics of the economy (Bloom and Canning [21]). Among notable studies, Barro and Sala-i-Martin [12], Bloom and Sachs [13] and Bhargava, Dean, Jamison, Murray [30] and Gyimah-Brempong and Wilson [31] show that the correlation between better health and higher economic growth holds up even when additional economic variables are introduced to try to account for the cross-country patterns of growth.

Additional evidence of the importance of health for economic growth has been provided by international organizations. For instance, a report by the World Health Organization's Commission on Macroeconomic and Health demonstrates significant linkages of health with economic growth, and health and poverty (WHO [32]). Similarly, studies conducted by the Pan American Organization show long-term impacts of life expectancy on economic growth in Mexico and Latin American countries (Mayer-Foulkes [33], Mayer-Foulkes [34]). These initiatives, besides generating an enormous amount of high quality research, have served to fill a void in the existing literature (Lo´pez-Casasnovas, Rivera and Currais [22]).

Finally, a variety of methodological techniques have been employed in the literature to examine the relationship between these two variables (Bhat and Jain [10]). Of interest in this paper are time series approaches; and a variety of different time series tests have been used. For instance, Arora [9] has explored the cointegrated relation between health and income using health-related variables for nine advanced economies, concluding that innovations in health lead to economic growth, and not vice-versa. Similarly, Hansen and King [3] and Blomqvist and Carter [4] detected unit roots in health care expenditures and GDP, but were not able to find cointegration in general, as a long run relationship seemed to exist only for a few countries. Other notable time series studies include Okunade and Karakus [35], Gerdtham and Löthgren [6], McCoskey and Selden [5], Hansen and King [36], Im, Pesaran and Shin [37], and Jewell, Lee, Tieslau and Strazicich [38]. While some insights have been gained from these studies, the focus has been on national economies, either in developed or developing countries. This paper explores this relationship at the U.S. state-level using time series analysis.

III. DATA

State personal health care expenditure (PHCE) data covering the period 1980-2004 were obtained from the Center for Medicare and Medicaid Services (CMMS [39]), while data on gross state product (GSP) for the same period were obtained from the U.S. Bureau of Economic Analysis (BEA [40]). States for which meaningful data series could be constructed include: Alabama, Florida, Georgia, Louisiana, Mississippi and Tennessee.

Like at the national level, personal health care expenditure across the selected southeast U.S. states has steadily increased over time. As can be seen in Fig. (**1**), the nation and respective southeast states exhibited different patterns of growth during the study period. For instance, the U.S. had an average annual economic growth rate (GDP) of 5.3 percent and an average annual growth rate for personal health care expenditure of 6.9 percent. States with economic growth

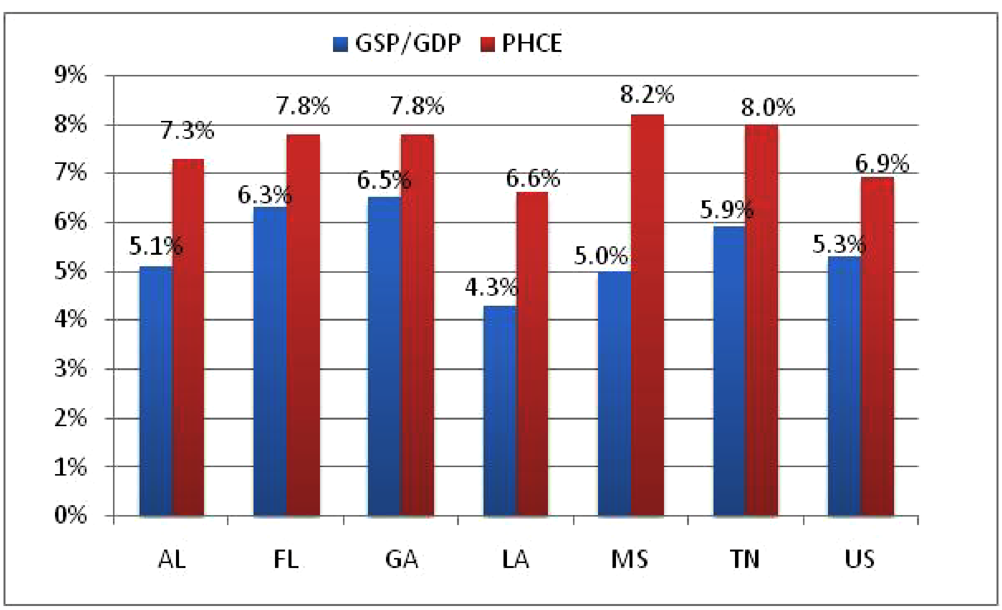

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Fig. (1). Average annual growth rates for PHCE and GSP 1990-2004.

(GSP) rates exceeding the U.S. average economic growth (GDP) rate include Florida, Georgia and Tennessee, while Alabama, Mississippi and Louisiana experienced subpar economic growth, as measured by GSP.

Looking at personal health care expenditure, only Louisiana had an average annual growth rate (6.6 percent) lower than the U.S. rate. The rest of the selected southeast U.S. states had higher growth rates, about 1 percent point higher than the U.S. average growth rate in personal health care spending. Overall, growth in personal health care spending was consistently above economic growth in the U.S. and across the southeast states. As noted by Glied [41], the rapid growth in health spending relative to U.S. and state incomes is raising concerns among federal and state policy makers and others as to whether the U.S. health care system is financially sustainable. Moreover, it is anticipated that this trend will continue unless significant policy measures are enacted (Glied [41]).

The data also reveals some variations in the share of income spent on health care. For a fifteen year average (1990-2004), the U.S. spent 11 percent of its GDP on personal health care (Fig. **2**). Georgia is the only southeast state with personal health care expenditure, as a share of GSP, similar to that of the U.S., while the shares of Alabama, Florida, Louisiana, Mississippi and Tennessee exceed the U.S. share. Overall, the states that spent relatively higher shares of GSP on personal health care expenditure include Alabama, Florida and Mississippi, all with an average share of 15 percent.

IV. TESTING FOR TRENDS

To account for the time structure of *Personal health care expenditure* (*PHCE*) and *Gross state product* (*GSP*) variables, unit root tests are conducted using the Augmented Dickey-Fuller method; hereafter ADF (Dickey and Fuller [42, 43], Davidson and MacKinnon [44]). Whether or not to include the linear trend in conducting unit root tests is still contentious. For instance, McCoskey and Selden [5] indicated that the ADF regressions should not include any linear trend, because the intercept itself already acts as a trend and power is lost in the case of a limited sample. To the contrary, Hansen and King [34] argued that the time trend is evident for these variables and must be included to apply the ADF test in its general form. In this paper, unit root tests are performed using equations that incorporate a constant and trend. The non-rejection of the null hypothesis for the unit root indicates that the series is characterized by a random walk representation (Dickey and Fuller [43], Davidson and MacKinnon [44]).

Table **1** show the unit root test results for the level series, as well as their first differences. MacKinnon's critical values for testing the null hypothesis for the unit root at the 5 percent and 10 percent levels when a constant and trend are included are -3.645 and -3.260, respectively, for the level series, and -3.659 and -3.268, respectively for the first-differenced series. For the level series, the null hypothesis of the unit root cannot be rejected for personal health care expenditure and GSP series at both the 5 percent and 10 percent significance levels. For the first differences of personal health care expenditure, the null hypothesis of the unit root is rejected for Georgia, at the 5 percent significance level; and for Alabama, Louisiana, Mississippi and Tennessee, at the 10 percent significance level. This suggests that, the values of personal health care expenditure in these states are I(1), because their first differences are stationary. To the contrary, the null hypothesis of the unit root cannot be rejected for the first differences for Florida at the 10 percent level or higher. In fact, personal health care expenditure series for Florida are I(2), because the second difference are stationary with an ADF statistic of -5.099.

As regards the first differences for the GSP series, they are stationary in three states, Alabama, Louisiana and Mississippi, at the 5 percent significance level and in two states, Georgia and Tennessee at the 10 percent significance level; they are non-stationary for Florida. Again, the second differ-

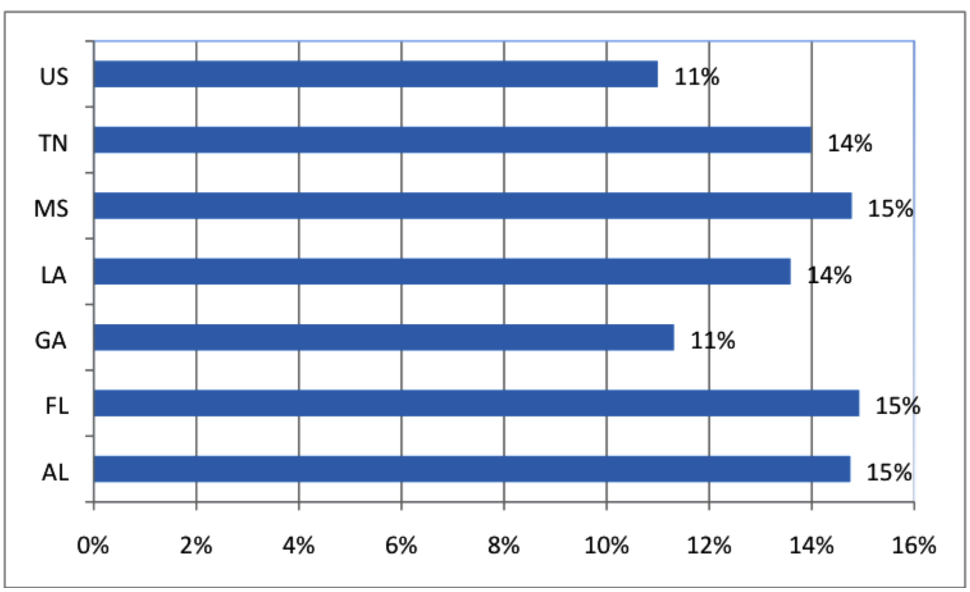

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Fig. (2). Variation in % of PHCE as a share of GSP/GDP (1990-2004 average).

ence for GSP series for Florida are I(2), with an ADF statistic of -4.225.

Table 1. Augmented Dickey-Fuller (ADF) Test Results

	Personal Health Care Expenditure		Gross State Product	
	Levels	First-Differences	Levels	First-Differences
AL	-1.722	-3.359*	0.463	-4.023**
FL	1.290	-1.196	2.135	-0.976
GA	-0.014	-7.909**	-0.605	-3.531*
LA	-2.700	-3.558*	-1.350	-4.712**
MS	1.699	-3.313*	-1.786	-4.352**
TN	0.377	-3.301*	-0.512	-3.478*

*, ** indicates significance at 10% and 5% levels, respectively.
Note: With constant and trend.

V. COINTEGRATION ANALYSIS

Next, cointegration analysis is conducted for those series found to be I(1) based on the ADF test. To accomplish this, the Engle-Granger [43] two-step test is employed. If a series Y_t is non-stationary and there is a β vector (or matrix) such that $W_t = \beta' Y_t$ becomes stationary, then Y_t is considered cointegrated and the vector β is called the cointegrating vector (Engle and Granger [43]). Previously in Table 1, it was shown that both personal health care expenditure series ($PHCE_t$) and gross state product series (GSP_t) are I(1) when a constant and trend are included for Alabama, Georgia, Louisiana, Mississippi, and Tennessee series. Thus, these non-stationary series can be written as a linear combination of stationary and non-stationary series as:

$$\begin{aligned} PHCE_t &= a_{11}\phi_t + a_{12}\varpi_t \\ GSP_t &= a_{21}\phi_t + a_{22}\varpi_t \end{aligned} \tag{1}$$

where ϕ_t and ϖ_t represent the unit root and stationary component, respectively.

Since each component of the bivariate series includes the nonstationary component ϕ_t, both components of Y_t are nonstationary. However, if the coefficients $(a_{ij}, i, j = 1, 2)$ are known, then

$$PHCE_t - \frac{a_{21}}{a_{11}} GSP_t = \left(a_{22} - \frac{a_{21}a_{12}}{a_{11}} \right) \varpi_t = c\,\varpi_t \tag{2}$$

is stationary and the system is cointegrated with the cointegrating vector $\beta = \left(-\frac{a_{21}}{a_{11}} , 1 \right)'$. Since we do not know the coefficients, we normally need to estimate all the coefficients in equation (1). But now, it is sufficient only to estimate the ratio $\frac{a_{21}}{a_{11}}$ using OLS (Engle and Granger [45]**)**. The differenced series in (2) look like the residuals from the regression of $PHCE_t$ on GSP_t, and hence if the residual series is stationary, then the bivariate series is cointegrated. Moreover, the OLS estimator of the parameter $PHCE_t$ obtained from that regression is a consistent estimator for the ratio $\frac{a_{21}}{a_{11}}$. The results for the cointegration equations when GSP_t is regressed on $PHCE_t$ and vice-versa are reported in Table **2**.

To check for cointegration, the errors from the cointegration equations are recovered to perform nonstationarity tests since cointegration requires stationary residuals (Engle and Granger [45]). To do that, the following equation is specified:

$$\Delta\varepsilon_t = \varpi\varepsilon_{t-1} + \sum_{i=1}^{p} \psi_i \Delta\varepsilon_{t-i} + \eta_t \tag{3}$$

where ε_t is the error from the cointegration equation, η_t is a stationary random error; here the null hypothesis of non-stationarity is rejected when ϖ is significantly negative. The summation runs to 'p' where p is 2. Table **3** reports the ADF test statistics and the critical values. As shown in Table **3**, the null hypothesis of non-stationary of the residuals cannot be rejected at the 5 percent significance level for both personal health care expenditure and GSP series for all states, except Georgia. Thus, the cointegration results

Table 2. Co-Integration Regression

State	PHCE Regressed on GSP			GSP Regressed on PHCE			R-Square
	β-Coef.	t-Ratio	D-W Test	β-Coef.	t-Ratio	D-W Test	
AL	5.152*	58.49	0.602	0.193*	58.49	0.602	0.993
GA	8.016*	35.44	0.335	0.123*	35.44	0.335	0.982
LA	4.242*	19.30	0.754	0.222*	19.30	0.754	0.941
MS	4.560*	32.98	0.254	0.215*	32.98	0.254	0.993
TN	5.854*	58.79	0.652	0.170*	58.79	0.652	0.993

* Denotes significance at 1% level.

suggest that a long-run relationship between PHCE and GSP seems to exist only for Georgia.

Table 3. ADF Test on Residuals

State	PHCE Regressed on GSP	GSP Regressed on PHCE	5 % Critical Value
AL	-2.748	-2.745	-3.2474
GA	-3.657*	-3.654*	-3.2474
LA	-2.051	-2.104	-3.2474
MS	-0.955	-0.905	-3.2474
TN	-2.095	-2.070	-3.2474

* Significant at 5% critical values.
Note: Estimates based on Level series.

VI. TESTING FOR CAUSALITY

The interrelationship between personal health care expenditure and gross state product can be more directly examined using causality and Vector Autoregression Analysis (VAR). By incorporating time lags between these variables, these approaches are particularly relevant because changes in personal health care expenditure typically my not cause changes in economic growth immediately, but rather over several periods and vice-versa.

The standard Granger causality test (Granger [46]) examines whether past changes in one variable, y, help to explain current changes in another variable, x, over and above the explanation provided by the past changes in x. If not then one concludes that y does not Granger causes x. To determine whether causality runs in the other direction, from x to y, one simply repeats the experiment, but with y and x interchanged. Four findings are possible: 1) neither variable Granger causes the other; 2) y causes x, but not vice versa; 3) x causes y, but not vice versa; and 4) y and x Granger causes each other (Granger [46]).

The estimated Granger causality test is based on the following regression (Granger [46]):

$$\Delta PHCE_t = \alpha_0 + \sum_{i=1}^{m} \beta_i \Delta PHCE_{t-i} + \sum_{i=1}^{m} \delta_i \Delta GSP_{t-i} + \varepsilon_t \quad (4)$$

where Δ is the first-difference operator and Δ PHCE and Δ GSP are stationary time series. The null hypothesis that GSP does not Granger causes PHCE is rejected if the coefficients δ_i in equation (4) are jointly significant based on the standard F-test. The null hypothesis that PHCE does not Granger causes GSP is rejected if the β_is are jointly significant in equation (4), when $\Delta PHCE_t$ replaces ΔGSP_t as the left-hand side variable (Granger [46]). Table **4** reports the F-statistics for the standard Granger causality tests of whether personal health care expenditure causes economic growth or vice versa, which provides a benchmark for our VAR analysis.

At the conventional 5 percent significance level, the standard causality tests suggest that we cannot reject the null hypothesis that personal health care expenditure does not Granger causes economic growth for Alabama and Louisiana (Table **4**). For Georgia, Mississippi and Tennessee, the results suggest that personal health care expenditure Granger causes economic growth, as measured by GSP. As for the null hypothesis that GSP does not Granger causes personal health care expenditure, the null hypothesis is rejected only for Georgia, implying the existence of a feedback effect between GSP and personal health care expenditure in Georgia.

Since the null hypotheses that GSP does not Granger causes personal health care expenditure, and vice versa cannot be rejected at the conventional 5 percent significance level for Alabama and Louisiana, it can be concluded that neither variable Granger causes the other in these states. Also, since the null hypothesis that GSP does not Granger causes personal health care expenditure cannot be reject for Mississippi and Tennessee at the conventional 5 percent significance level while the null hypothesis that personal health care expenditure does not Granger causes GSP was rejected at the conventional 5 percent significance level, it can be concluded that personal health care expenditure Granger causes GSP, but not vice versa (Table **4**).

Table 4. Pair wise Granger Causality Tests

Null Hypothesis:	F-Statistic	Probability
Alabama:		
PHCE does not Granger Cause GSP	0.423	0.739
GSP does not Granger Cause PHCE	2.087	0.145
Georgia:		
PHCE does not Granger Cause GSP	4.358*	0.029
GSP does not Granger Cause PHCE	3.307*	0.060
Louisiana:		
PHCE does not Granger Cause GSP	1.901	0.178
GSP does not Granger Cause PHCE	0.171	0.845
Mississippi:		
PHCE does not Granger Cause GSP	8.148*	0.003
GSP does not Granger Cause PHCE	0.241	0.788
Tennessee:		
PHCE does not Granger Cause GSP	4.872*	0.020
GSP does not Granger Cause PHCE	1.209	0.322

* Significance at 5% level.

VII. VECTOR AUTO REGRESSION

The VAR approach provides a useful means of analyzing the broad correlation in the variables of a system. In the current context, VAR analysis can be used to highlight the impact of changes in personal health care expenditure on economic growth (GSP) in two ways: decomposition of the variance into forecast errors and secondly the analysis of

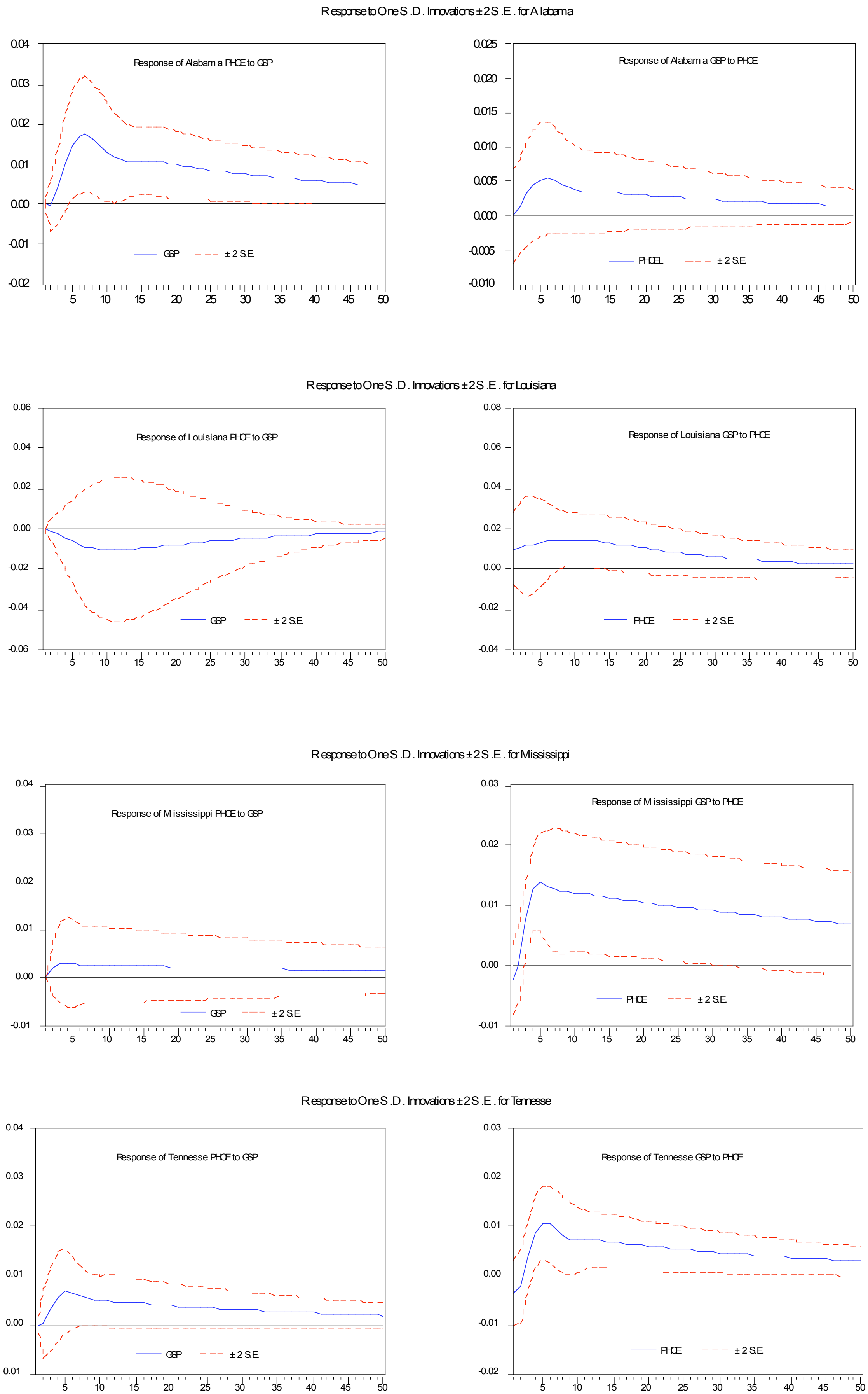

Fig. (3). Impulse function results.

impulse shocks. It sidesteps the need for structural modeling by modeling every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. For this purpose, estimated VARs can be used to calculate the percentages of each endogenous variable that are explained by innovations in each of the other endogenous, as well as the explanatory variables, and provide information about the relative importance of each random innovation to the variable in the VAR. The mathematical form of a VAR is as follows (EViews [47]):

$$Y_t = A_1 Y_{t-1} + ... + A_p Y_{t-p} + \beta X_t + \varepsilon_t \quad (5)$$

where Y_t is a k vector of endogenous variables, X_t is a d vector of exogenous variables, $A_1, ..., A_p$ and β are matrices of coefficients to be estimated, and ε_t is a vector of innovations that may vary contemporaneously.

The present interest is in discovering the lags and the signs of these lags, as they measure the impacts of persoanl health care expenditure changes on economic growth and vice versa. This is best accomplished through impulse response functions that simulate the impacts of a shock of a given variable (leaving all variables endogenous) and then compute the predicted dynamic responses of each of the included variables. By treating the residuals of each equation as unexplained innovations, the impacts of innovations are traced through the system by shocking the error terms (Hamilton [48]). To employ the impulse functions, the VAR equations are first estimated and the impulse response computed. The lack of strong cointegration between the endogenous variables in four of the six series (Alabama, Lousiana, Tennessee and Mississippi) permit us to procede in this direction. Because some nonstationarity was found in the time series of these variables, it is best to ensure stationarity by using some transform, in this case percentage changes.

In order to use the estimated VAR to analyze the interaction between personal health care expenditure and gross state product in the structural models, impulse-response functions are computed by recovering structural innovations from the estimated residuals (linear combinations of uncorrelated structural shocks) coming from the VAR (Hamilton [48]). The computed impulse functions (which show the difference between the expected value of the variable at time $t + i$ after a hypothetical shock at time t, and the expected value of the same variable at time $t + i$ given the observed history of the system) for each equation for Alabama, Louisiana, Tennessee and Mississippi are presented in Fig. (**3**).

By looking at the impulse response functions, there is evidence in favor of personal health care expenditure positively affecting economic growth. Positive changes in PHCE are shown to increase economic growth for up to five periods in Alabama, Mississippi and Tennesse and up to ten periods in Louisiana. Lag dependency is strongest for Louisiana at five periods but declines sharply by the sixth period. The explanations for Mississippi and Tennessee are the next best. Here the lag dependency declines slowly and is sustained for several periods. Lag dependency for Alabama are the weakest and shown to decline by the sixth period.

Similarly, there is some evidence in favor of economic growth positively affecting personal health care expenditure. Positive changes in GSP are shown to increase personal health care expenditure for up to five periods in Alabama and Tennessee, and up to three periods in Mississippi. To the contrary, positive changes in GSP are shown to have a negative effect on personal health care expenditure in Louisiana. Lag dependency is strongest for Louisiana at ten periods followed by Alabama at six periods, but declines sharply by the seventh period. The explanations for Tennessee is the next best with Mississippi having the weakest lag dependency, but does declines very slowly for several periods.

CONCLUSION

In this paper, an attempt was made to find the direction of the causal relationship between personal health care expenditure and economic growth, measured by gross state product, in the southeast United States. The empirical results of univariate and multivariate time series analysis suggest that only a weak relationship can be confirmed. After detecting unit roots in health care expenditures and GSP, we were not able to find cointegration in general, as a long run relationship seemed to exist only for Georgia. This finding is similar to earlier country studies (Hansen and King [3], Blomqvist and Carter [4]) that were not able to find cointegration in general, as a long run relationship after detecting unit roots in health care expenditure and GDP.

The results for Granger Causality test suggested the existence of a feedback effect between GSP and personal health care expenditure for Georgia, and a unidirectional effect for Mississippi and Tennessee indicating that personal health care expenditure Granger causes GSP, but not vice versa. To the contrary, the results for Alabama and Louisiana suggest that neither variable Granger causes the other. The results of the VAR analysis are correspondingly limited. However, the shapes of the impulse functions do confirm the proper positive relationship between positive personal health care expenditure changes and economic growth in all the states except Louisiana, where positive changes in GSP are shown to have a negative effect on PHCE. Overall, the impulse function results, albeit weak, show that innovations in personal health care expenditure lead to economic growth and vice versa for Mississippi, Tennessee, Louisiana, and Alabama.

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