A Panel Data Approach for Income-Health Causality

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Abstract

This study provides evidence on income-health causality by employing a large micro panel data set with a VAR representation. The findings verify that dominant type of causality is bidirectional which cast doubt on the performance OLS estimates in the literature. Moreover, one-way causality pattern is not similar for different income groups. One-way causality generally runs from income to health in low- and middle-income countries whereas the reverse holds for high-income countries.

Keywords: Income, Health, Granger Causality.
JEL Classification: C20; I10.

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1 Introduction

Theoretical literature on health-income relationship suggests that there must be a bi-directional relationship between health and income. First, by definition, health (expenditure) is a function of resources available (income or wealth). Second, a reverse causation, income as a function of health (expenditure), has also a theoretical basis due to the fact that the latter is a determinant of (i) human capital, and (ii) labor-supply and productivity. If health (expenditure) can be regarded as an investment in human capital (Mushkin, 1962; Fuchs, 1966; Grossman, 1972; van Zon and Muysken, 2001), and given that human capital is an "engine" of growth (Lucas, 1988), an increase in health (expenditure) must ultimately lead to higher income achievements. Similarly, rises in health (expenditure) make possible higher labor supply and productivity, which eventually must give way to a higher income (*e.g.*, Muysken, Yetkiner, and Ziesemer (2003)).

The relationship between health and economic development has been empirically investigated intensely as well. Firstly, several works such as Newhouse (1977), Leu (1986), Parkin *et al*. (1987), Posnett and Hitiris (1992), Pritchett and Summers (1996) Hansen and King (1996), and Barros (1998), studying the impact of income on health (at rather macro level), consistently found a strong effect of income in explaining health differences.[1] Secondly, since Barro (1991) and Barro and Sala-i-Martin (1992), several studies have investigated the positive effect of health on economic development, especially in the context of "conditional convergence", using health proxies for explaining the long-run growth differences across countries (*e.g.*, Knowles and Owen, 1995 and 1997). Results suggest a strong and robust effect of health in explaining income per capita differences.

The problem in both strands of literature is that the OLS estimation will produce biased and inconsistent estimates of the structural parameters, if what theory suggests that there is an endogenous relationship between income and health is true (*cf.*, Rivera and Currais (1999) and Devlin and Hansen (2001)). Therefore, it is vitally critical to determine in advance what kind of (Granger) causality relationship exists between health and income. To our knowledge, there are very few studies in that direction and the evidence is mixed. For example, Devlin and Hansen (2001) tested (Granger) causality between health expenditure and GDP in order to examine the exogeneity of the latter and showed some (mixed) evidence that indeed there might be bi-directional (Granger) causality between health (expenditure) and income. Nevertheless, their findings could not be considered complete due to the small size of their dataset. In this study, we employ a larger data set and consequently a more refined technical analysis to verify the direction of (Granger) causality between health and income. We find that bi-directional causality is the leading type of causality for our sample of 75 countries, though it is not homogenous. We also show that the one-way causality pattern is different for different income groups.

The organization of the paper is as follows. Section 2 presents empirical tests on the direction of causality. Section 3 presents our main conclusions.

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[1] See Strauss and Thomas (1998) for a general survey of the literature and footnote 1 in Adams *et al*. (2003) for studies associating a link between health and income rather at micro level.

2 A Panel Data Approach

2.1 The Methodology

The literature generally does not provide diversified methods for Granger (1969) causality tests in panel data models. It is possible to classify mainly two types of approaches. The first one is pioneered by Holtz-Eakin *et al*. (1985), which considers estimation and testing vector autoregression (VAR) coefficients in panel data letting the autoregregressive coefficients and regression coefficients slopes as variable. A more or less similar procedure is applied by Hsiao (1986), Holtz-Eakin *et al*. (1988), Hsiao (1989), Weinhold (1996), Weinhold (1999), Nair-Reichart and Weinhold (2001), and Choe (2003). The second approach proposed by Hurlin and Venet (2001), Hurlin (2004a), Hurlin (2004b), Hansen and Rand (2004) treats the autoregregressive coefficients and regression coefficients slopes as constant. In this study, we employ the second approach because of its suitability to our data sets, in which we have relatively short time periods whereas large number of cross-section units. Following Hurlin and Venet (2001), we consider two covariance stationary variables, denoted by x and y, observed on T periods and on N cross-section units. In the context of Granger (1969) causality procedure, for each individual $i \in [1,N]$, the variable $x_{i,t}$ is causing $y_{i,t}$ if we are better able to predict $y_{i,t}$ using all available information than if the information apart from $x_{i,t}$ had been used. In practice, it will not usually be possible to use completely optimum predictors, so we consider only linear ones. For this reason, we are concerned about a time-stationary VAR representation, used for a panel data set. For each cross-section unit *i* and time period *t*, we estimate the following model:

$$y_{i,t} = \sum_{k=1}^{p} \beta_k y_{i,t-k} + \sum_{k=0}^{p} \theta_k x_{i,t-k} + u_{i,t} \qquad (1)$$

where $u_{i,t} = \alpha_i + \varepsilon_{i,t}$ and $\varepsilon_{i,t}$ are *i.i.d.* $(0, \sigma^2)$. It is assumed that the autoregressive coefficients β_k and the regression coefficients θ_k's are constant for $k \in [1,N]$. Moreover, it is further assumed that parameters β_k are identical for all individuals, while the coefficients θ_k could have an individual dimensions. In other words, the model utilized in this study is panel data model with fixed coefficients. Finally, the residuals are assumed to satisfy the standard properties. The use of panel data dimension has a number of advantages. First, it provides a large number of observations. Second, it increases the degrees of freedom. Finally, it reduces the collinearity among explanatory variables. In sum, it obviously improves the efficiency of Granger causality tests (Hurlin and Venet, 2001). In testing causality with panel data, the researcher should pay attention to the question of heterogeneity between cross-section units. The first source of heterogeneity is caused by permanent cross sectional disparities. A pooled estimation without heterogeneous intercepts leads to a bias of the slope estimates and could lead to a fallacious inference in causality tests (Hurlin, 2004a). Another basis of heterogeneity caused by heterogeneous regression coefficients θ_k is more problematic than the first one. In sum, the analysis of causality for panel data sets should consider the different sources of heterogeneity of the data-generating process. Therefore, there are different types of causality hypothesis to be

tested in a panel data set framework.[1] The first test procedure, named as homogenous and instantaneous non-causality hypothesis (HINC), is directed towards testing whether or not the θ_k's of $x_{i,t-k}$ are simultaneously null for all individual i and all lag k. The hypotheses to be tested are:

$$H_0 : \theta_k = 0 \ \forall i \in [1, N], \forall k \in [0, p] \qquad (2)$$
$$H_1 : \theta_k \neq 0 \ \ \exists (i, k)$$

For testing Np linear restrictions in (2), the following Wald statistics is calculated:

$$F_{HINC} = \frac{(SSR_r - SSR_u)/(Np)}{SSR_u / [NT - N(1+p) - p]} \qquad (3)$$

where SSR_u stands for the sum of squared residuals for model in (1) and SSR_r for the restricted sum of squared residuals under H_o. If individual effects, α_i, are assumed to be fixed, SSR_u and SSR_r are SSR obtained from the maximum likelihood (ML) estimation that corresponds in this case to the fixed effects (FE) estimator.

If the HINC hypothesis is rejected, there are two possibilities. The first one is the homogenous causality hypothesis (HC) and takes place if all the coefficients θ_k are identical for all lag k and are statistically different from zero. In other words, we are testing whether or not θ_k's in (1) are equal to each other. The following hypotheses are tested:

$$H_0 : \theta_k^i = \theta_k^j \ \forall i, j \in [1, N], \forall k \in [0, p] \qquad (4)$$
$$H_1 : \theta_k^i \neq \theta_k^j \quad \exists (i, j, k)$$

In order to test (4), the following statistics is calculated:

$$F_{HC} = \frac{(SSR_r^{'} - SSR_u)/[p(N-1)]}{SSR_u / [NT - N(1+p) - p]} \qquad (5)$$

where $SSR_r^{'}$ is the restricted sum of squared residuals under H_o. As in the case of HINC, if individual effects, α_i, are assumed to be fixed, the ML estimator is consistent with the FE estimator.

If the HC hypothesis is also rejected, this means that the process is non-homogenous and no homogenous causality relationships can be obtained. Nonetheless, such a situation need not entail the lack of any causality relationships between two variables. It may still be possible that for one or more cross-section units, there exist causality relationships. Hence, the variable x causes the variables y only for a subgroup of cross-section units. The last step is to test heterogeneous non-causality hypothesis (HENC). The hypotheses under this case are:

$$H_0 : \theta_i^k = 0 \ \forall i \in [1, N], \forall k \in [0, p] \qquad (6)$$

[1] For a detailed discussion of those tests and finite sample properties, see Hurlin and Venet (2001).

$$H_1 : \theta_i^k \neq 0 \; \forall i \in [1, N], \forall k \in [0, p]$$

In other word, for each cross-section unit, the nullity of all the coefficients of the lagged explanatory variable $x_{i,t-k}$ are tested. For testing (6), the following statistics is calculated:

$$F_{HENC} = \frac{(SSR_r'' - SSR_u)/p}{SSR_u/[NT - N(1+2p) + p]} \tag{7}$$

where SSR_r'' is sum of squared residuals found in (1) when the nullity of the k coefficients associated with the variable $x_{i,t-k}$ only for the cross-section unit i are imposed. These N individual tests identify the cross-section unit for which there are no causality relationships. If the HENC hypothesis is not rejected, this means that there exists a subgroup of cross-section units for which the variable x does not cause the variable y. This hypothesis can be analyzed as the consequence of the heterogeneity of the data-generating process. The causality relationship is relevant only for a subgroup of cross-section units.

As using micro-panels, where there are large number of cross-section units and small number of time series observations, the FE estimator of the coefficients of lagged endogenous variables is biased and inconsistent (Nickell, 1981). On the other hand, the ML estimators for dynamic fixed effects models remains biased with the introduction of exogenous variables when T is small (Hurlin and Venet, 2001). Moreover, Kiviet (1995) also provides an analytical expression for this bias. However, Nickell (1981) demonstrates a fall in the size of bias on the coefficients of lagged endogenous variables with the presence of exogenous regressors. Furthermore, Judson and Owen (1999) provide Monte Carlo evidence and show that FE estimator's bias decreases with T. Thus, for our case, we have decided to use FE estimator provided that the bias may not be large. Finally, there is one more point to note that Wald test statistics do not have a standard distribution under H_o when T is small (Hurlin and Venet, 2001). Hurlin (2004a) provides exact critical values for Wald statistics for testing causality in micro panels.

2.2 The Data and the Model

The data of our study in an attempt to test the bidirectional causality between real per capita GDP and real per capita health expenditures in a panel data setting are derived from World Bank's World Development Indicators, 2002. According to their GNI, the World Bank classifies countries into four categories, namely low-income, lower middle-income, upper middle-income, and high income countries. After eliminating the countries with missing observations, we have included 19 low-income (LIC), 22 lower middle-income (LMIC), 10 upper middle-income (UMIC), and 24 high-income countries (HIC) for the period 1990-2000. However, the relatively low number of upper middle-income countries forces us to combine lower middle-income and upper middle-income as a one group named as middle-income (MIC) group with 32 countries. Therefore, we have a balanced panel data set for real GDP per capita (GDP) and real health expenditures per capita (H) on 75 countries between 1990 and 2000. The list of countries included in our data set is presented at appendix A.

The following two models are estimated for each of three groups:

$$\Delta GDP_{i,t} = \sum_{k=1}^{p} \beta_k \Delta GDP_{i,t-k} + \sum_{k=0}^{p} \theta_k \Delta H_{i,t-k} + u_{i,t} \quad (8)$$

$$\Delta H_{i,t} = \sum_{k=1}^{p} \beta_k \Delta H_{i,t-k} + \sum_{k=0}^{p} \theta_k \Delta GDP_{i,t-k} + u_{i,t} \quad (9)$$

For both variables, we take natural logarithms. We further difference the data in order to eliminate possible unit roots. Thus, our variables are, in fact, growth rates. Before estimating equations (8) and (9), the number of lags is determined for both variables in each country group using Akaike Information Criteria (AIC). However, because of the shortness of time series in our data set, we use rather a different methodology in selecting lag length. We start with the first lag and continue with the second until we reach minimum AIC; yet we stop at the third lag whether we reach minimum AIC or not.

Following the estimation of (8) and (9), we test both homogenous and instantaneous non-causality (HINC) and homogenous causality (HC) hypotheses. Later, the models for testing heterogeneous non-causality hypothesis (HENC) are estimated and HENC hypotheses are tested for each country group.

2.3 Bidirectional Causality between Health and Income: Pooled Estimation

As a first step to explore the bidirectional causality between health and income, the lag lengths are chosen for both variables. Table 1 presents AIC figures for each country group. Consequently, for LIC, we choose three lags for GDP and two lags for H. In the case of MIC, two lags for GDP and one lag for H are chosen. Finally, for HIC, the corresponding lag lengths are one and three respectively.

Table 1 is about here

After choosing the lag lengths, equations (8) and (9) are estimated for each country group in order to test HINC and HC hypothesis. The results of the estimation are presented at appendix B. Table 2 demonstrates the values of F statistics given by (3) and (5) for testing two types of homogenous causality hypothesis, namely HINC and HC. The test results cause us to reject both of the null hypotheses at 1% level of significance which means that there is no homogenous causality between GDP and H. The hypotheses belonging to HIC are rejected at 5%. In other words, rejecting the null hypothesis of HINC means that there exists a causality relation between GDP and H. The next question is whether the causality is an overall (homogenous) causality for each country group or sourced from causality relations for individual countries (heterogeneous). The results verify the existence of a heterogeneous causality as a result of testing HC hypothesis.

Table 2 is about here

The next step for an attempt to search for causality is to detect the individual countries' contribution to the existence of causality. For this end, we estimate equations (8) and (9) where θ_k's differ among countries in our data set and HENC

hypotheses are tested for each individual country. The results of F_{HENC} test given in (7) are presented at Table 3 and the detailed F-statistics are shown at appendix C.[1]

Table 3 is about here

According to Table 3, for 46 countries out of 75 bidirectional causality relation is observed meaning that for around 61% of the countries in our data set bidirectional causality both from *GDP* to *H* and *H* to *GDP* is relevant. In the context of country groups, the shares of bidirectional causality are observed at 68%, 65%, and 50% for LIC, MIC, and HIC, respectively. We have six exceptions of bidirectional causality for LIC. Causality relation from *GDP* to *H* is detected for Ghana, Mozambique, Nigeria, and Togo; and causality from *H* to *GDP* is seen only for Burkina Faso while no causality relation is observed in either direction for Zimbabwe. In the case of MIC, for six countries out 32, namely Botswana, Bulgaria, Costa Rica, Ecuador, Sri Lanka, and Thailand, only causality from *GDP* to *H* is found. The reverse causality is obtained for Brazil and Venezuela. Finally, for Honduras, Romania, and Syria there is no causality relationship between *GDP* and *H*. Since data collection may not be reliable in these countries, especially in Romania and Syria because of their specific characteristics, we believe that these three countries are ignorable. For HIC, the bidirectional causality is found for 12 out of 24 countries. Moreover, for the one-way causality, the pattern is different as compared to LIC and MIC. The causality from *H* to *GDP* is dominant for HIC, that is to say an increase in growth rate of H causes more probably an increase in GDP in HIC. For Belgium, Germany, Japan, New Zealand, Spain, and Sweden, the causality runs from *H* to *GDP*. Only for Austria and Ireland, we observe causality running from *GDP* to *H*. Finally, no causality is perceived in either direction for Australia, Israel, and Singapore. We argue the finding that a higher share of HIC show *H* to *GDP* causality may be a signal of structural differences between HIC and MIC and LIC. Firstly, advanced economies are more human capital dependent than LIC and MIC. In that respect, it is natural to find that health (Granger) causes income in HIC. Secondly, given that public share of health expenditures are substantially higher in HIC relative to MIC and HIC, a positive externality might exist that blurs the impact of income on health. Thirdly, HIC have better public infrastructure, another source of externality, which may lower the significance of income in explaining health due to the fact that a good infrastructure diminishes the risk of epidemics, accidents, cost of catastrophes, etc. Hence, data may not be able to show a causality running from income to health.

3 Concluding Remarks

We applied Granger causality approach to panel data model with fixed coefficients in order to determine the relation between GDP and health expenditures per capita. The results of testing HINC hypothesis show us the existence of bidirectional causality for our sample. However, this causality is not homogenous which is evident from the tests of HC hypotheses. The tests for heterogeneous causality present that the leading type of causality is bidirectional. For one-way causality, the pattern of causality is different in LIC and MIC as compared to HIC. One-way causality generally runs from GDP to H in LIC and MIC whereas the reverse is valid for HIC. Our contribution to the

[1] The estimation output for this test can be requested from authors.

literature is to show a stronger evidence of bi-directional (Granger) causality running between health expenditure and income for a larger set of countries and by more refined econometric techniques. A further prospect for this type of study is to repeat the tests proposed here with longer time series. This will be possible whenever United Nations produces consistent time series data on national financial accounts.

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Table 1 *Number of Lags for GDP and H*

Country Group	Variable	LAG1	LAG2	LAG3	LAG4	# of Lags
LIC	GDP	-3.244	-3.387	-3.657	-3.823	3
	H	0.154	0.146	0.184		2
MIC	GDP	-3.171	-3.868	-3.853		2
	H	0.802	0.818			1
HIC	GDP	-4.926	-4.865			1
	H	-1.645	-1.679	-1.720	-1.730	3

Table 2 *Test results for Homogenous Causality Hypotheses*

Country Group	Test	Causality from H to GDP	Causality from GDP to H
LIC	HINC	11.41**	11.97**
	HC	15.92**	6.44**
MIC	HINC	8.99**	133.70**
	HC	17.96**	129.59**
HIC	HINC	15.75**	3.47*
	HC	63.02**	6.38*

**Reject H_0 at 5% level of significance, **Reject H_0 at 1% level of significance.*

Table 3 *Test results for Heterogeneous Causality Hypotheses*

Low Income Countries	Direction	Middle Income Countries	Direction	High Income Countries	Direction
Bangladesh	Bidirectional	Argentina	Bidirectional	Australia	No causality
Burkina Faso	H to GDP	Bolivia	Bidirectional	Austria	GDP to H
Burundi	Bidirectional	Botswana	GDP to H	Belgium	H to GDP
Cameroon	Bidirectional	Brazil	H to GDP	Canada	Bidirectional
Cote d'Ivoire	Bidirectional	Bulgaria	GDP to H	Denmark	Bidirectional
Ethiopia	Bidirectional	Chile	Bidirectional	Finland	Bidirectional
Ghana	GDP to H	China	Bidirectional	France	Bidirectional
Haiti	Bidirectional	Colombia	Bidirectional	Germany	H to GDP
Indonesia	Bidirectional	Costa Rica	GDP to H	Greece	Bidirectional
Kenya	Bidirectional	Dominic	Bidirectional	Ireland	GDP to H
Mali	Bidirectional	Ecuador	GDP to H	Israel	No causality
Mozambique	GDP to H	El Salvador	Bidirectional	Italy	Bidirectional
Nigeria	GDP to H	Guatemala	Bidirectional	Japan	H to GDP
Pakistan	Bidirectional	Honduras	No causality	Korea	Bidirectional
P. New Guinea	Bidirectional	Iran	Bidirectional	Netherlands	Bidirectional
Senegal	Bidirectional	Jamaica	Bidirectional	New Zealand	H to GDP
Tanzania	Bidirectional	Jordan	Bidirectional	Norway	Bidirectional
Togo	GDP to H	Malaysia	Bidirectional	Portugal	Bidirectional
Zimbabwe	No causality	Mexico	Bidirectional	Singapore	No causality
		Namibia	Bidirectional	Spain	H to GDP
		Panama	Bidirectional	Sweden	H to GDP
		Paraguay	Bidirectional	Switzerland	Bidirectional
		Peru	Bidirectional	United Kingdom	H to GDP
		Philippines	Bidirectional	United States	Bidirectional
		Poland	Bidirectional		
		Romania	No causality		
		Sri Lanka	GDP to H		
		Syria	No causality		
		Thailand	GDP to H		
		Turkey	Bidirectional		
		Uruguay	Bidirectional		
		Venezuela	H to GDP		

Appendix A *Countries in the Data Set*

Low Income Countries	**Middle Income Countries**	**High Income Countries**
Bangladesh	Argentina	Australia
Burkina Faso	Bolivia	Austria
Burundi	Botswana	Belgium
Cameroon	Brazil	Canada
Cote d'Ivoire	Bulgaria	Denmark
Ethiopia	Chile	Finland
Ghana	China	France
Haiti	Colombia	Germany
Indonesia	Costa Rica	Greece
Kenya	Dominic	Ireland
Mali	Ecuador	Israel
Mozambique	El Salvador	Italy
Nigeria	Guatemala	Japan
Pakistan	Honduras	Korea
Papua New Guinea	Iran	Netherlands
Senegal	Jamaica	New Zealand
Tanzania	Jordan	Norway
Togo	Malaysia	Portugal
Zimbabwe	Mexico	Singapore
	Namibia	Spain
	Panama	Sweden
	Paraguay	Switzerland
	Peru	United Kingdom
	Philippines	United States
	Poland	
	Romania	
	Sri Lanka	
	Syria	
	Thailand	
	Turkey	
	Uruguay	
	Venezuela	

Appendix B1 *Estimation Results of VAR Equation from Health to GDP*

LIC			**MIC**			**HIC**		
Variable	Coefficient	HC.Std. Error	Variable	Coefficient	HC.Std. Error	Variable	Coefficient	HC.Std. Error
DLGDP(-1)	0.074633	0.089923	DLGDP(-1)	0.112613	0.051421	DLGDP(-1)	0.279074	0.057285
DLGDP(-2)	-0.022048	0.059812	DLGDP(-2)	0.009189	0.027209	DLH	0.01236	0.012223
DLGDP(-3)	0.015959	0.052171	DLH	0.012324	0.00366	DLH(-1)	-0.048198	0.0067
DLH	0.037328	0.009528	DLH(-1)	-0.013894	0.003809	DLH(-2)	0.009783	0.007261
DLH(-1)	0.007959	0.00632				DLH(-3)	-0.018543	0.008608
DLH(-2)	-0.003038	0.005312						
Fixed Effects			Fixed Effects			Fixed Effects		
BAN--C	0.029093		ARG--C	0.009836		AUS--C	0.019662	
BUF--C	0.020386		BOL--C	0.012305		AUT--C	0.017483	
BUR--C	-0.029904		BWA--C	0.024095		BEL--C	0.020917	
CAM--C	0.01367		BRA--C	0.011784		CAN--C	0.021067	
COT--C	0.016033		BGR--C	0.005176		DNK--C	0.020205	
ETH--C	0.018949		CHL--C	0.034384		FIN--C	0.031906	
GHA--C	0.02942		CHN--C	0.071896		FRA--C	0.01672	
HAI--C	-0.007965		COL--C	0.005506		DEU--C	0.014485	
IND--C	0.016001		CRI--C	0.023508		GRC--C	0.021196	
KEN--C	-0.000368		DOM--C	0.03833		IRL--C	0.062363	
MAL--C	0.022049		ECU--C	-0.011657		ISR--C	0.016438	
MOZ--C	0.047526		SKU--C	0.018775		ITA--C	0.012753	
NIG--C	0.00808		GTM--C	0.012162		JPN--C	0.011235	
PAK--C	0.013396		HND--C	0.000954		KOR--C	0.037072	
PAP--C	-0.008925		IRN--C	0.012919		NLD--C	0.020553	
SEN--C	0.025177		JAM--C	-0.006824		NZL--C	0.014749	
TAN--C	0.011621		JOR--C	0.001622		NOR--C	0.021031	
TOG--C	0.022001		MYS--C	0.033953		PRT--C	0.026371	
ZIM--C	0.015463		MEX--C	0.015402		SGP--C	0.032816	
Adi. R^2	0.59928		NAM--C	0.01932		ESP--C	0.02139	
N	133		PAN--C	0.020487		SWE--C	0.02171	
			PRY--C	-0.003939		CHE--C	0.008797	
			PER--C	0.024733		GBR--C	0.021911	
			PHL--C	0.012508		USA--C	0.019935	
			POL--C	0.043697		Adi. R^2	0.632014	
			ROM--C	0.005245		N	168	
			LKA--C	0.034762				
			SYR--C	0.006232				
			THA--C	0.023263				
			TUR--C	0.014445				
			URY--C	0.012252				
			VEN--C	-0.014132				
			Adi R^2	0.606004				
			N	256				

Appendix B2 *Estimation Results of VAR Equation from GDP to Health*

LIC			**MIC**			**HIC**		
Variable	Coefficient	HC.Std. Error	Variable	Coefficient	HC.Std. Error	Variable	Coefficient	HC.Std. Error
DLGDP	2.38853	0.484575	DLGDP	1.996631	0.100059	DLGDP	1.228487	0.600588
DLGDP(-1)	1.034685	0.308204	DLGDP(-1)	-0.430108	0.125467	DLGDP(-1)	-0.79543	0.336945
DLGDP(-2)	0.775601	0.243237	DLGDP(-2)	0.23232	0.090711	DLH(-1)	0.122235	0.066191
DLGDP(-3)	0.462639	0.221846	DLH(-1)	0.083723	0.053535	DLH(-2)	-0.424346	0.054097
DLH(-1)	-0.179822	0.06083				DLH(-3)	0.154675	0.065585
DLH(-2)	-0.266	0.048328						
Fixed Effects			Fixed Effects			Fixed Effects		
BAN--C	-0.121544		ARG--C	-0.055814		AUS--C	-0.010623	
BUF--C	-0.265182		BOL--C	-0.047332		AUT--C	-0.022279	
BUR--C	-0.152867		BWA--C	-0.0608		BEL--C	-0.013086	
CAM--C	-0.07998		BRA--C	-0.734191		CAN--C	-0.026542	
COT--C	-0.263662		BGR--C	-0.604403		DNK--C	-0.022297	
ETH--C	-0.130041		CHL--C	-0.057029		FIN--C	-0.03638	
GHA--C	-0.488578		CHN--C	-0.0823		FRA--C	-0.027429	
HAI--C	-0.055034		COL--C	-0.048358		DEU--C	-0.021674	
IND--C	-0.259818		CRI--C	-0.127625		GRC--C	-0.058641	
KEN--C	-0.069639		DOM--C	-0.024235		IRL--C	0.005724	
MAL--C	-0.094994		ECU--C	-0.391045		ISR--C	0.005742	
MOZ--C	-0.417898		SKU--C	0.029374		ITA--C	-0.047774	
NIG--C	-0.399788		GTM--C	-0.018398		JPN--C	0.024342	
PAK--C	-0.161371		HND--C	-0.136336		KOR--C	-0.022767	
PAP--C	-0.199312		IRN--C	-0.374248		NLD--C	-0.036913	
SEN--C	-0.222984		JAM--C	0.003035		NZL--C	-0.001226	
TAN--C	-0.134385		JOR--C	0.015092		NOR--C	0.006666	
TOG--C	-0.174055		MYS--C	-0.07399		PRT--C	-0.004323	
ZIM--C	-0.348895		MEX--C	-0.153082		SGP--C	0.029774	
Adi. R^2	0.26659		NAM--C	-0.102119		ESP--C	-0.029549	
N	133		PAN--C	-0.0072		SWE--C	-0.014853	
			PRY--C	-0.05398		CHE--C	0.002678	
			PER--C	-0.182791		GBR--C	0.02409	
			PHL--C	-0.054217		USA--C	0.006099	
			POL--C	-0.191068		Adi. R^2	0.235137	
			ROM--C	-0.556243		N	168	
			LKA--C	-0.089236				
			SYR--C	-0.144785				
			THA--C	-0.135611				
			TUR--C	-0.519393				
			URY--C	-0.129818				
			VEN--C	-0.252939				
			Adi R^2	0.491771				
			N	256				

Appendix C1 *Test results for Heterogeneous Causality from H to GDP*

LIC		MIC		HIC	
Bangladesh	2.30*	Argentina	9.88***	Australia	0.97
Burkina Faso	127.27***	Bolivia	5.38***	Austria	1.61
Burundi	13.38***	Botswana	0.02	Belgium	97.50***
Cameroon	133.27***	Brazil	15.30***	Canada	31.05***
Cote d'Ivoire	4.17***	Bulgaria	2.05	Denmark	5.27***
Ethiopia	10.99***	Chile	15.98***	Finland	3.01**
Ghana	188.33***	China	3.30**	France	1309.06***
Haiti	17.26***	Colombia	21.47***	Germany	140.04***
Indonesia	62.60***	Costa Rica	1.42	Greece	1414.12***
Kenya	23.47***	Dominic	6.73***	Ireland	0.08
Mali	6.94***	Ecuador	1.43	Israel	1.29
Mozambique	1.76	El Salvador	0.12	Italy	1213.9***
Nigeria	1.39	Guatemala	261.74***	Japan	1071.1***
Pakistan	363.88***	Honduras	1.49	Korea	56.95***
Papua New Guinea	6.28***	Iran	22.50***	Netherlands	226.86***
Senegal	19.50***	Jamaica	76.13***	New Zealand	1941.22***
Tanzania	2.80**	Jordan	11.45***	Norway	17.44***
Togo	1.90	Malaysia	7.14***	Portugal	2.22*
Zimbabwe	0.45	Mexico	277.22***	Singapore	0.31
		Namibia	21.27***	Spain	76.43***
		Panama	4.06**	Sweden	86.50***
		Paraguay	9.27***	Switzerland	13.02***
		Peru	12.29***	United Kingdom	406.59***
		Philippines	9.09***	United States	3793.12***
		Poland	5.64***		
		Romania	1.23		
		Sri Lanka	1.35		
		Syria	0.45		
		Thailand	0.56		
		Turkey	14.92***		
		Uruguay	9.27***		
		Venezuela	5.77***		

**Reject H_0 at 10% level of significance, **Reject H_0 at 5% level of significance, ***Reject H_0 at 1% level of significance.*

Appendix C2 *Test results for Heterogeneous Causality from GDP to H*

Low Income Countries		**Middle Income Countries**		**High Income Countries**	
Bangladesh	57.31***	Argentina	4.74***	Australia	0.05
Burkina Faso	1.01	Bolivia	7.83***	Austria	7.97***
Burundi	6.73***	Botswana	31.61***	Belgium	0.45
Cameroon	588.36***	Brazil	0.26	Canada	2.93*
Cote d'Ivoire	450.41***	Bulgaria	6.74***	Denmark	10.96***
Ethiopia	2.66**	Chile	40.36***	Finland	4.73**
Ghana	0.28	China	7.50***	France	4.29**
Haiti	1101.2***	Colombia	19.07***	Germany	0.56
Indonesia	468.25***	Costa Rica	32.05***	Greece	145.88***
Kenya	126.99***	Dominic	238.02***	Ireland	14.44***
Mali	717.78***	Ecuador	18.88***	Israel	0.47
Mozambique	372.17***	El Salvador	103.87***	Italy	12.37***
Nigeria	251.05***	Guatemala	4.77***	Japan	1.70
Pakistan	7.81***	Honduras	1.73	Korea	635.67***
Papua New Guinea	2.92**	Iran	14.43***	Netherlands	21.23***
Senegal	222.51***	Jamaica	4.66***	New Zealand	1.81
Tanzania	103.17***	Jordan	256.39***	Norway	4.89***
Togo	797.70***	Malaysia	295.71***	Portugal	3.18**
Zimbabwe	1.21	Mexico	13.55***	Singapore	1.10
		Namibia	123.92***	Spain	0.99
		Panama	3.37**	Sweden	0.30
		Paraguay	2.72**	Switzerland	6.50***
		Peru	2.48*	United Kingdom	1.18
		Philippines	425.71***	United States	74.70***
		Poland	125.67***		
		Romania	1.27		
		Sri Lanka	33.50***		
		Syria	0.09		
		Thailand	93.10***		
		Turkey	4.81***		
		Uruguay	2.44*		
		Venezuela	0.63		

**Reject H_0 at 10% level of significance, **Reject H_0 at 5% level of significance, ***Reject H_0 at 1% level of significance.*