Human capital, energy and economic growth in China

– Evidence from multivariate nonlinear Granger causality[1]

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Abstract: Using the recently developed nonlinear multivariate Granger causality test by Diks and Wolski (2015) and an augmented production function which incorporates both physical and human capital, this study investigates the causal link between economic development and aggregate and disaggregate energy consumption in China during the period of 1965-2014. This is the first time the nonlinear Granger causal test is applied to a multivariate framework in the energy-growth nexus literature and human capital is accounted for in the Chinese context. Our results confirm the neutrality hypothesis for both aggregate energy use and coal, natural gas and hydroelectricity consumption, while unidirectional causality running from GDP to oil is found using the nonlinear approach. Weak evidence on the substitution effect between human capital and energy/coal is also observed in the linear approach. These imply that energy conservation policies are feasible in China and policies advocating the improvement of human capital associated with energy-specific skills may be helpful as well in reducing pollution.

Key words: Multivariate nonlinear causality test, human capital, energy-growth nexus, China

JEL classification codes: Q43, Q48, C50

[1] Any views expressed are only those of authors and do not represent the views of the EIB.

1. Introduction

Human capital has long been recognized as an important contributor to the economic growth (Lucas, 1988; Barro, 1991; Mankiw, et al., 1992; Aghion and Howitt, 2009). According to the World Bank, human capital, rather than physical capital, exerts the greatest influence on economic growth throughout the world (Auty, 2001). However, in the burgeoning literature on the energy-growth nexus (see Ozturk, 2010; Omri, 2014 for a review), we can hardly find any studies which have taken this factor into consideration. One exception is Pablo-Romero and Sánchez-Braza (2015) who used an aggregate translog production function, with human and physical capital and productive energy use as factor inputs to estimate the role of energy in economic growth. Their results suggest the presence of a strong substitution effect between human capital and energy and imply that training of the workers could reduce the energy use. Another exception is Fang and Chang (2016) who studied the energy-growth causal link in the Asia Pacific region by considering both the impact of human capital and the cross-country dependence. Their results support the conservation hypothesis in the Asia Pacific region but conclusions vary across countries.[2]

Indeed, human capital may be associated with energy consumption in many ways. On the one hand, it can promote the research and development of new energy-efficient technologies, and help a nation catch up with the existing advanced technologies. Human capital may also be positively associated with public awareness of the importance of energy saving, which also contributes to the negative relationship between human capital and energy consumption. On the other hand, development of human capital could stimulate the change of economic structure and accelerate industrialization. Therefore, a positive association between human capital and energy consumption is also possible. Due to the offsetting

[2] As pointed out by Fang and Chang (2016), one of the reasons that human capital is seldom taken into consideration in this strand of literature may be the lack of reliable data on the human capital variable. The recently built human capital index by Feenstra et al. (2015), however, makes more studies on this topic possible and thus we expect that the role of human capital in the link of energy and growth will draw more attention and investigation.

effects, the existence and direction of a causal relationship between energy consumption and human capital deserve rigorous investigation.[3]

This study aims to investigate the energy-growth relationship in China through a prism of an augmented production function, which additionally takes into consideration the role of human capital and energy. In particular, we study the latter at the aggregate and disaggregate levels, i.e. the total energy consumption and its sector-specific components in the coal, oil, natural gas and hydroelectricity sectors. We take China as the case study because of its economic and energy profiles in the world picture. China, as the second largest economy in the world, contributes 22.4% of total world primary energy consumption and 27.1% of greenhouse gas emission in 2013 (BP Statistics Review of World Energy 2014), making it the top energy consumer and carbon dioxide emitter in the world. Moreover, China is the largest consumer of coal and the second-largest consumer of oil in the world (EIA, 2014). Its energy-growth relationship is, therefore, of worldwide concern for scholars and policy makers.

This study contributes to the existing energy-growth nexus literature in China by highlighting the role of human capital in the multivariate framework. Previous studies which consider physical capital, labor and energy as inputs in the energy-augmented production function have come to mixed results of the directions of Granger causality between energy consumption and GDP (see the appendix Table A1 for a brief summary); also they have ignored impacts of changes in skills, knowledge and environmental protection and energy saving consciousness of labor on the energy demand and economic development.

The second major contribution of this study is its methodological approach. On top of standard linear methods, we also apply a novel nonlinear multivariate Granger causality framework, developed recently by Diks and Wolski (2015) (DW thereafter). DW test is a multivariate extension of the Diks and Panchenko (2006) nonlinear Granger causality framework. The latter has been already widely used in empirical literature (see Chiou-Wei et al., 2008; Bekiros and Diks, 2008), because of its power and much better performance than an earlier method proposed by Hiemstra and Jones (1994). However, the test has

[3] Human capital has received a lot of attention in the more recent literature (see for instance Zivin et al., 2015).

consistent asymptotic properties only in a bivariate setting, making it cumbersome to extend to multivariate applications.[4] DW test offers a relief by providing a fully consistent multivariate testing methodology. Results from the DW test tend to be more reliable because of two reasons: first, the linear Granger causality test may fail to capture the nonlinear predictive power; second, there is an increasing empirical evidence on the existence of nonlinearity in energy and economic development variables in the literature (Lee and Chang, 2007). To our best knowledge, this is one of the first attempts to study the energy-growth nexus through a prism of correctly-specified nonlinear multivariate methods.

The remainder of the study is organized as follows: Section 2 describes the data and outlines the econometric methodologies; results and discussions are presented in section 3; and section 4 concludes with policy implications.

2. Data and methods

2.1 Data

This study uses annual time series data of China retrieved from the Penn World Table version 9.0 (Feenstra et al., 2015) and British Petroleum's 2015 Statistical Review of World Energy. Real gross domestic product (GDP) and physical capital are in million US$ at the constant 2005 prices. Human capital stock is converted to the aggregate level by multiplying the human capital index with the employment level (measured in millions). All these variables are from the Penn World Table version 9.0. Due to the way how human capital stock is constructed, we use a four-variable framework which includes physical and human capital, energy and real GDP to investigate the energy-growth nexus in China.

It is worthwhile explaining human capital index further given its importance in this study. Human capital index (*hc*) in the Penn World Table version 9.0 is constructed as follows:

$$hc = e^{\phi(s)}$$

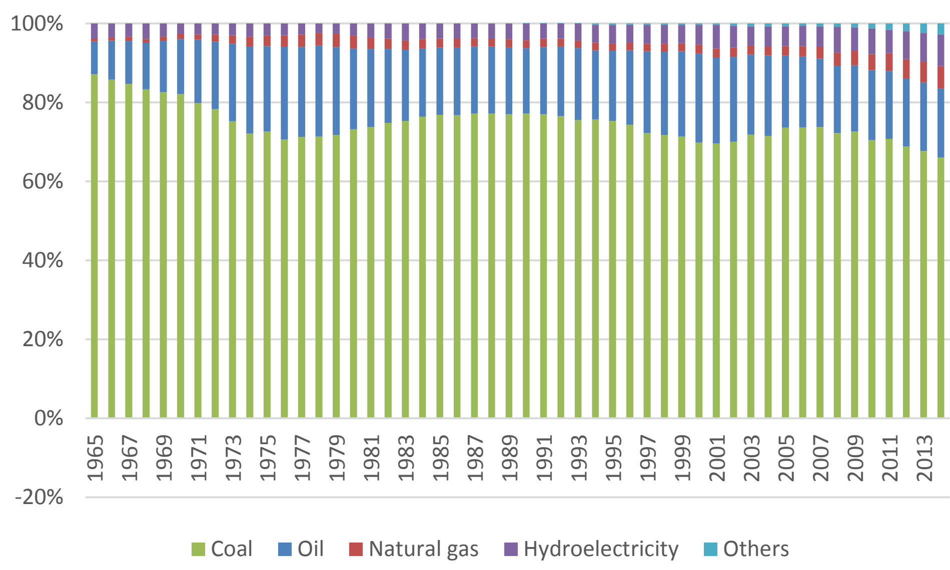
[4] For instance, one could project the multivariate setting on a bivariate plane before performing the test. Nevertheless, such methods can suffer from substantial information losses and, as a consequence, they can lead to biased inference.

where s is the average years of schooling for the working-age population (aged 15 and above) and $\phi(s)$ is a piece-wise linear function which is given below:[5]

$$\phi(s) = \begin{cases} 0.134s & \text{if } s \leq 4 \\ 0.134 * 4 + 0.101(s-4) & \text{if } 4 < s \leq 8. \\ 0.134 * 4 + 0.101 * 4 + 0.068(s-8) & \text{if } s > 8 \end{cases}$$

Energy to be examined in this study includes not only the aggregate energy consumption but the disaggregate energy consumption as well, including the consumption of coal, oil, natural gas and hydroelectricity. Nuclear and renewables consumption constitute only 3% of the total energy consumption in 2014, and even less in early years, so they are excluded from the analysis. All the energy consumption is measured in million-tons oil equivalent (mtoe) and taken from the British Petroleum's 2015 statistical review of world energy. Using all observations available, this study covers a period of 1965-2014. Figure 1 shows clearly that coal is the primary energy type but its share in the energy mix is decreasing over time. On the other hand, the share of hydroelectricity consumption has been steadily increasing from less than 4% in 1965 to 8% in the most recent year.

Figure 1: Share of energy consumption in China



[5] It is assumed rates of return vary for different years of education (Caselli, 2005, Psacharopoulos, 1994). More discussion on the human capital index measure refers to Inklaar and Timmer (2013) and Fang (2016).

All the variables are expressed in natural logarithms so that the first differences approximate the growth rate. The notations are as follows: lnGDP denotes log of real GDP, lnK and lnH denotes log of physical and human capital stocks, and lnE, lnCoal, lnOil, lnGas, and lnHydro are logs of the aggregate energy, coal, oil, gas and hydroelectricity consumption, respectively. Summary statistics of the variables are given in the Appendix Table A2.

Figure 2 shows the growth rates of China's real GDP and aggregate energy consumption for the period of 1966-2014. It is evident that the growth patterns of the two series are closely correlated. In most of the years, economic growth rate is larger than growth rate of energy consumption; and energy consumption seems to be more volatile. Figure 3 shows the evolution of employment level and human capital during the period. Given the measure of human capital used in this study (human capital index times employment level) and human capital index is larger than 1, it is expected that human capital is larger than employment level, as can be seen in Figure 3. Furthermore, Figure 3 shows that human capital has a steeper growth than employment level. This suggests that prior multivariate framework using labor input may have ignored important implications from the over-time change in human capital.

Figure 2: Growth rate of GDP and energy consumption (%)

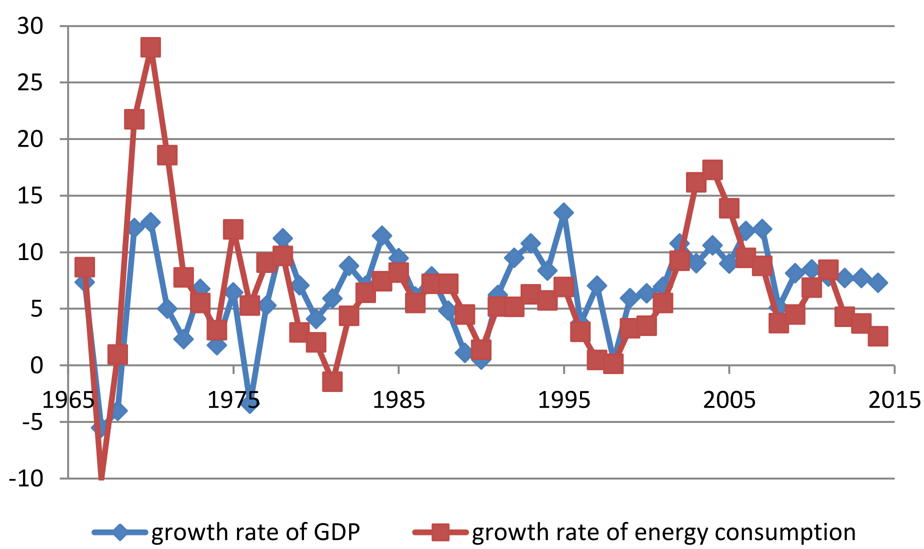
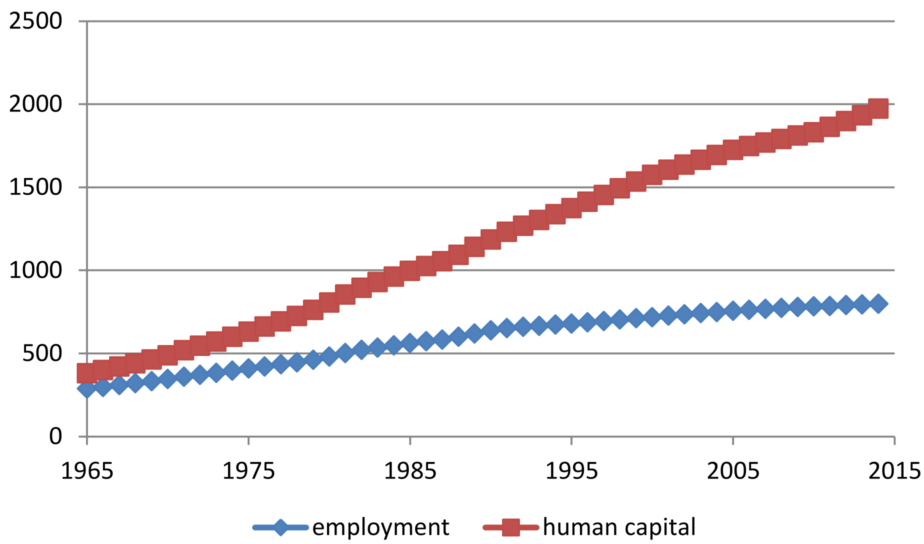


Figure 3: Evolution of human capital and employment



2.2 Econometric methods

We analyze both linear and nonlinear causal relationship between energy consumption and economic growth in China for a period of 1965-2014 using an augmented production function which considers the role of human capital. In doing so, we first carry out unit root and Johansen cointegration tests for the variables of interest. After that, VECM is applied for the linear Granger causality test and recently developed Diks and Wolski (2015, DW hereafter) method is used for the nonlinear Granger causality test.

2.2.1 Tests for stationarity

We check the stationarity of the variables using four unit root tests: augmented Dickey and Fuller (1979) tests, Dickey-Fuller tests with GLS detrending (Elliott et al., 1996), Philips and Perron (1988) tests and Kwiatkowski-Philips-Schmidt-Shin tests (Kwiatkowski et al., 1992). The first three have the null hypothesis of a unit root against stationarity, while the KPSS assumes stationary series under the null.

2.2.2 Tests for cointegration

This study applies the Johansen cointegration test (Johansen and Juselius, 1990) to test for cointegration; because unlike Engle-Granger test, it enables identification of more than one cointegrating relationship and allows testing restrictions imposed on the long-run coefficients.

If all the variables in $\mathrm{X_t}$ are $\mathrm{I}(1)$, according to the Granger representation theorem, the vector $\mathrm{X_t}$ has a vector error correction (VEC) representation as follows:

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta X_{t-i} + \mu + \epsilon_t$$

where Δ is a difference operator, X is a $4 \text{ X } 1$ vector containing $\mathrm{lnGDP}, \mathrm{lnK}, \mathrm{lnH}$ and one of the energy variables lnE, lnCoal, lnOil, lnGas, and lnHydro, $\Pi = \sum_{\mathrm{i=1}}^{\mathrm{p}} \mathrm{A_i} - \mathrm{I}$ and $\Gamma_\mathrm{i} = -\sum_{\mathrm{j=i+1}}^{\mathrm{p}} \mathrm{A_j}$. If the rank of Π equals the number of variables which is four in our case, the variables are stable in levels and there is no cointegration. If the rank of Π equals zero, the VEC specification is reduced to an unrestricted VAR and none of the linear combinations are stationary. If the rank of Π equals r where $0 < r < 4$, the matrix Π can be decomposed into $\alpha\beta'$ with α and β both 4 X r matrices. The matrix $\alpha = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)'$ represents the speed of adjustment, and the cointegrating matrix $\beta = (\beta_1, \dots, \beta_\mathrm{r})$ indicates the long-run equilibrium. The Johansen test uses a maximum likelihood method to estimate the cointegrating rank r and parameters α and β. The model can therefore be expanded as follows:

$$\Delta lnGDP_t = \mu_1 + \sum_{k=1}^{r} \alpha_{1,k}\beta_k' X_{t-1} + \sum_{s=1}^{p-1} \gamma_{11,s}\, \Delta lnGDP_{t-s} + \sum_{s=1}^{p-1} \gamma_{12,s}\, \Delta lnK_{t-s} + \sum_{s=1}^{p-1} \gamma_{13,s}\, \Delta lnH_{t-s} + \sum_{s=1}^{p-1} \gamma_{14,s}\, \Delta lnE_{t-s} + \epsilon_{1,t}$$

$$\Delta lnK_t = \mu_2 + \sum_{k=1}^{r} \alpha_{2,k}\beta_k' X_{t-1} + \sum_{s=1}^{p-1} \gamma_{21,s}\, \Delta lnGDP_{t-s} + \sum_{s=1}^{p-1} \gamma_{22,s}\, \Delta lnK_{t-s} + \sum_{s=1}^{p-1} \gamma_{23,s}\, \Delta lnH_{t-s} + \sum_{s=1}^{p-1} \gamma_{24,s}\, \Delta lnE_{t-s} + \epsilon_{2,t}$$

$$\Delta lnH_t = \mu_3 + \sum_{k=1}^{r} \alpha_{3,k}\beta_k' X_{t-1} + \sum_{s=1}^{p-1} \gamma_{31,s}\, \Delta lnGDP_{t-s} + \sum_{s=1}^{p-1} \gamma_{32,s}\, \Delta lnK_{t-s} + \sum_{s=1}^{p-1} \gamma_{33,s}\, \Delta lnH_{t-s} + \sum_{s=1}^{p-1} \gamma_{34,s}\, \Delta lnE_{t-s} + \epsilon_{3,t}$$

$$\Delta lnE_t = \mu_4 + \sum_{k=1}^{r} \alpha_{4,k}\beta_k' X_{t-1} + \sum_{s=1}^{p-1} \gamma_{41,s}\, \Delta lnGDP_{t-s} + \sum_{s=1}^{p-1} \gamma_{42,s}\, \Delta lnK_{t-s} + \sum_{s=1}^{p-1} \gamma_{43,s}\, \Delta lnH_{t-s} + \sum_{s=1}^{p-1} \gamma_{44,s}\, \Delta lnE_{t-s} + \epsilon_{4,t}$$

where $\beta_k' X_{t-1} (k = 1\ to\ r)$ denotes the k-th cointegrating equations. Each of the cointegrating vector indicates the existence of a stable long-run equilibrium state. Deviation from its long-run equilibrium will feed back on its future changes to bring its movement back to the long-run equilibrium state, and the proportion corrected in each short-term period is represented by coefficients of the error-correction terms α. A joint test proposed by Johansen (1992) is employed to determine the model specification and the cointegrating rank r.

The Johansen cointegration test is to estimate the matrix Π from an unrestricted VAR and test the restriction implied by the reduced rank Π based on the trace test and maximum eigenvalue test as follows:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln\left(1 - \lambda_i^2\right);\ \lambda_{max}(r, r+1) = -Tln(1 - \lambda_{r+1})$$

Where λ_i is the ordered eigenvalue obtained from the estimated matrix and T is the number of usable observations after lag adjustment. The number of cointegrating relations is determined by proceeding sequentially from $r = 0$ to $r = k - 1$ until the null hypothesis cannot be rejected. The null hypothesis of the trace statistic is r cointegrating relations against the alternative of more than r cointegrating relations; and the null hypothesis of the maximum eigenvalue statistic is r cointegrating relations against the alternative of $r + 1$ cointegrating relations.

2.2.3 Tests for linear and nonlinear Granger causality

We test both the linear and nonlinear Granger causal relationship among the four variables of interest. For the linear Granger causality test, the VEC model can be applied when the variables are cointegrated. We examine the statistical significance of all lagged dynamic terms of the independent variable. If $\gamma_{ij,s}(s = 1,2 \dots p - 1) \neq 0$, there exists a (short-run) Granger causal relationship running from variable j to variable i. The long-run Granger causality is tested by examining the significance of the speed of adjustment coefficients α or by performing the joint test of the lagged independent variables and the error correction term ($\beta_k^{'} X_{t-1}$ in the VECM specification). For instance, if $\alpha_{1,k}(k = 1,2 \dots r)$ and $\gamma_{14,s}(s = 1,2 \dots p - 1)$ are significantly different from zero, we will say that there exists a long-run Granger causality relationship running from energy consumption to economic growth.

Besides the linear Granger causality test, we conduct nonlinear Granger causality test proposed by DW. This is the first time the multivariate nonlinear Granger causality test is applied in the energy-growth nexus studies. The null hypothesis that energy does not Granger cause economic growth can be expressed as:

$$H_0: lnGDP_{t+1}|\left(lnE_t^{l_E}, lnGDP_t^{l_Y}, lnK_t^{l_K}, lnH_t^{l_H}\right) \sim lnGDP_{t+1}|\left(lnGDP_t^{l_Y}, lnK_t^{l_K}, lnH_t^{l_H}\right)$$

where '$\sim$' denotes equivalence in distribution and l_i $(i = E, GDP, K, H)$ represents the lag of the specific variable. Under the null hypothesis the series $\{lnE_t^{l_E}\}$ does not contain any additional information on the realizations of $lnGDP_{t+1}$besides information spanned by variables $\{lnK_t^{l_K}\}$ and $\{lnH_t^{l_H}\}$. To test for Granger causality between other pairs of variables we change the causality direction. For instance, to test whether economic growth Granger causes energy consumption, we reverse the direction as:

$$H_0: lnE_{t+1}\left|\left(lnGDP_t^{l_E}, lnE_t^{l_Y}, lnK_t^{l_K}, lnH_t^{l_H}\right) \sim lnE_{t+1}\right|\left(lnE_t^{l_Y}, lnK_t^{l_K}, lnH_t^{l_H}\right)$$

Formally, DW extend the nonlinear Granger causality testing approach proposed by Diks and Panchenko (2006) to the multivariate setting. The null hypothesis is tested over the conditional densities of variables of interest; however, to guarantee the consistency of the multivariate test statistic, the densities are evaluated at the sharpened data set. DW show that the test statistic is dominated by the bias component which in a multivariate setting increases disproportionally. The sharpening procedure reduces the estimator bias by providing more accurate point estimates with asymptotically unchanged variance, which eventually leads to a consistent test statistic. In line with DW, let $X_t = lnE_t$, $\boldsymbol{Y}_t = (lnGDP_t, lnK_t, lnH_t)$ and $Z_t = lnGDP_{t+1}$, and the compact form $W_t = (X_t, \boldsymbol{Y}_t, Z_t)$.The sharpened test statistic is

$$T_n^S(\varepsilon_n) = \frac{n-1}{n(n-2)} \sum_{t=1}^{n} [\hat{f}_{X,\boldsymbol{Y},Z}^S(X_t, \boldsymbol{Y}_t, Z_t)\hat{f}_{\boldsymbol{Y}}^S(\boldsymbol{Y}_t) - \hat{f}_{X,\boldsymbol{Y}}^S(X_t, \boldsymbol{Y}_t)\hat{f}_{\boldsymbol{Y},Z}^S(\boldsymbol{Y}_t, Z_t)]$$

In the statistic, $\hat{f}_W^s(W_t)$ is a sharpened form of the local density estimator of a d_W-variate vector W: $\hat{f}_W^s(W_t) = ((n-1)\varepsilon)^{-d_W} \sum_{k,k\neq t} K\left(\frac{W_t-\psi_p(W_k)}{\varepsilon_n}\right)$ where $K()$ is a density estimation kernel and $\psi_p()$ is a sharpening map used to reduce the bias of the estimator whose explicit form depends on order of bias reduction, determined by subscript p. DW prove that one can always find a sharpening function of order p for which there exists a sequence of bandwidths $\varepsilon_n = Cn^{-\beta}(C > 0, \frac{1}{2p} < \beta < \frac{1}{d_W})$ that guarantees that the sharpened test statistic satisfies:

$$\sqrt{n}\frac{(T_n^s(\varepsilon_n) - q)}{S_t} \xrightarrow{d} N(0,1)$$

where S_t^2 is a consistent estimator of the asymptotic variance of $\sqrt{n}(T_n^s(\varepsilon_n) - q)$ and q is defined as $E[f_{X,\boldsymbol{Y},Z}(X, \boldsymbol{Y}, Z)f_{\boldsymbol{Y}}(\boldsymbol{Y}) - f_{X,\boldsymbol{Y}}(X, \boldsymbol{Y})f_{\boldsymbol{Y},Z}(\boldsymbol{Y}, Z)]$.

One can easily verify that under the two-variable framework, i.e. when X_t and Y_t are both univariate, the optimal sharpening order is $p = 2$ and consequently there is no need to reduce the estimator bias, so that the test statistic is parallel to the popular one developed by Diks and Panchenko (2006).

3. Results and discussion

Following the methodology part, results of unit root tests, cointegration tests, and linear and nonlinear Granger causality tests are presented and discussed in this section.

3.1 Stationarity test results

Table 1 shows the results of the ADF, DF-GLS, PP and KPSS unit root tests in the level variables and their first differences. Two model specifications, one with only intercept and the other with both the intercept and trend, are presented. The results indicate that all variables are non-stationary in levels and the variables - lnGDP, lnE, lnCoal, lnOil and lnHydro - are stationary in first difference no matter which model specification is considered. So economic growth, aggregate energy consumption and disaggregate consumption in coal, oil and hydroelectricity are confirmed to be integrated of order one. lnK and lnH are found to be integrated of order one only when the model includes both intercept and time trend, and lnGas is first difference stationary in the model with intercept only. From a holistic perspective, we can conclude that all the variables are trend stationary in first differences. Therefore, we can investigate whether they are cointegrated using the Johansen cointegration test in the next step.

Table 1: Results of unit root tests

	Model with intercept				Model with intercept and trend			
	ADF	DF-GLS	PP	KPSS	ADF	DF-GLS	PP	KPSS
Level								
lnGDP	2.297	1.403	3.363	0.934***	-2.875	-1.731	-2.115	0.218***
lnK	3.740	0.094	8.278	0.936***	0.530	-1.383	0.082	0.242***
lnH	-3.534**	-0.282	-9.343***	0.917***	-0.871	-1.590	-0.132	0.244***
lnE	-2.227	1.090	-0.685	0.928***	-3.124	-3.070*	-2.079	0.100
lnCoal	-1.418	0.477	-0.569	0.927***	-3.420*	-3.478**	-2.259	0.085
lnOil	-1.731	0.609	-2.735*	0.902***	-2.500	-1.476	-2.968	0.115
lnGas	-0.735	0.499	-1.023	0.862***	-5.092***	-3.212**	-1.918	0.117
lnHydro	1.105	0.873	1.413	0.934***	-2.379	-2.142	-2.432	0.138*
First difference								
D(lnGDP)	-5.066***	-5.088***	-4.957***	0.481**	-5.642***	-5.535***	-5.806***	0.091
D(lnK)	-1.651	-1.464	-1.363	0.828***	-4.716***	-4.795***	-3.243*	0.110
D(lnH)	-1.178	-0.688	-0.959	0.857***	-3.814**	-3.544**	-2.940	0.077
D(lnE)	-3.771***	-3.767***	-3.154**	0.086	-3.743**	-3.814***	-3.079	0.065
D(lnCoal)	-3.988***	-4.032***	-3.388**	0.050	-3.951**	-4.038***	-3.331*	0.047
D(lnOil)	-3.894***	-2.464**	-3.975***	0.339	-4.014**	-3.638**	-4.128**	0.142*
D(lnGas)	-2.952**	-2.652***	-2.952**	0.178	-2.909	-2.875	-2.909	0.169**
D(lnHydro)	-7.713***	-7.155***	-7.726***	0.224	-7.906***	-7.934***	-7.951***	0.058

Notes: For Augmented Dickey-Fuller (ADF) and modified Dickey-Fuller (DF-GLS) tests, the maximum lag is set to four based on a $T^{1/3}$ rule. The optimal lag length is determined by the Schwarz information criterion (SIC). For Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, Bartlett kernel estimation method is chosen and the bandwidth is decided using the Newey and West method. ***,** and * denote the significance level at 1%, 5% and 10% respectively.

3.2 Cointegration test results

Since the Johansen result is sensitive to the choice of the lag length, we first determine the optimal lag length for the VAR (which is estimated with intercepts only) using the sequential modified likelihood ratio (LR), Akaike information criterion (AIC), SIC and Hannan-Quinn information criterion (HQ). As shown in Table 2, the optimal lag length for all the five set of variables is two. The choice of lag length is further validated by the normality and absence of serial correlation tests for the residuals of VAR model.

Table 2: VAR lag selection

Lag	LR	AIC	SIC	HQ
(a) (lnGDP, lnK, lnH, lnE)				
1	799.46	-22.29	-21.50	-22.00
2	80.19*	-23.77*	-22.33*	-23.23*
3	20.11	-23.68	-21.61	-22.91
4	11.19	-23.37	-20.67	-22.36
(b) (lnGDP, lnK, lnH, lnCoal)				
1	774.17	-21.69	-20.89	-21.39
2	75.41*	-23.03*	-21.60*	-22.49*
3	18.14	-22.88	-20.82	-22.11
4	11.07	-22.57	-19.87	-21.56
(c) (lnGDP, lnK, lnH, lnOil)				
1	829.67	-22.10	-21.31	-21.80
2	51.66*	-22.80	-21.37*	-22.27*
3	30.36	-23.03*	-20.96	-22.25
4	19.00	-22.99	-20.28	-21.97
(d) (lnGDP, lnK, lnH, lnGas)				
1	873.28	-21.84	-21.05	-21.54
2	65.50*	-22.92*	-21.49*	-22.38*
3	16.96	-22.73	-20.67	-21.96
4	17.18	-22.63	-19.93	-21.62
(e) (lnGDP, lnK, lnH, lnHydro)				
1	727.88	-20.50	-19.70	-20.20
2	59.53*	-21.41*	-19.98*	-20.88*
3	19.22	-21.30	-19.23	-20.52
4	10.14	-20.95	-18.25	-19.94

Note: * indicates lag order selected by the criterion.Column LR denotes the likelihood ratio test results, AIC stands for the Akaike information criterion, SIC for Schwarz information criterion and HQ for Hannan–Quinn information criterion.

Using a joint test to determine the cointegration rank and the model specification as discussed in Johansen (1992) and Ahking (2002), we find evidence of using the model with intercept in the cointegration equation and no constant in VAR. Based on this model specification, Table 3 presents Johansen and Juselies (1990) cointegration test results using trace statistics λ_{trace} and maximum eigenvalue statistic λ_{max}, respectively. Their corresponding critical values at the 5% significance level are also given in the table. For the model using either the aggregate energy consumption or the disaggregate energy consumption, the first hypothesis of $r = 0$ is rejected by both the trace and maximum eigenvalue statistics, while the second hypothesis of $r = 1$ cannot be rejected, suggesting the existence of one cointegrating vector. The evidence suggests, there is a linear combination of real GDP, physical capital, human capital and energy consumption (of both the aggregate and the disaggregate type) which is stable in the long run.

Table 3: Johansen cointegration test results

	lnE	lnCoal	lnOil	lnGas	lnHydro	0.05 critical values
(a) Trace statistics						
r=0 vs r≥1	66.781	63.150	67.104	65.829	64.524	54.079
r≤1 vs r≥2	32.183	29.081	34.205	33.248	28.615	35.193
r≤2 vs r≥3	18.549	16.941	19.328	16.536	16.370	20.262
r≤3 vs r≥4	6.700	6.260	6.180	7.422	7.523	9.165
(b) Max eigenvalue statistics						
r=0 vs r=1	34.598	34.070	32.899	32.582	35.909	28.588
r≤1 vs r=2	13.633	12.140	14.876	16.712	12.245	22.300
r≤2 vs r=3	11.849	10.680	13.149	9.114	8.847	15.892
r≤3 vs r=4	6.700	6.260	6.180	7.422	7.523	9.165

Note: The Johansen cointegration test results are based on the model with intercept in the cointegration equation and no constant in the VAR. The variables include lnGDP, lnK, lnH, and one of the energy variables lnE, lnCoal, lnOil, lnGas and lnHydro.

3.3 Linear and nonlinear Granger causality test results

Given the novelty of multivariate nonlinear Granger casusality test being applied to the economic growth-energy nexus literature, we first present the sharpened test statistics and associated p-values for various pairs of variables in Table 4. To determine the nature of Granger causality we apply the test on the raw and VECM-filtered data. Before applying the DW test, the data are standardized by a normal transformation. Since the DW test assumes stationarity of the underlying data, we consider the detrended first differences of original variables as inputs.[6] For transparency, we focus on pair-wise Granger causal relations, conditioning on the influence from other variables.

[6] The differenced data are not fully stationary. Therefore, to guarantee t the consistency of the nonlinear framework, we take into account detrended first differences as suggested by stationarity test results.

Table 4: Diks and Wolski (2015) multivariate nonlinear Granger causality test results

		Detrended first difference				VECM residuals			
X	Y	X→Y		Y→X		X→Y		Y→X	
		Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Energy	GDP	0.307	[0.379]	0.342	[0.366]	0.388	[0.349]	**1.414**	**[0.079]**
Coal	GDP	0.827	[0.204]	0.201	[0.420]	0.674	[0.250]	0.088	[0.465]
Oil	GDP	1.092	[0.137]	**1.401**	**[0.081]**	0.595	[0.276]	**1.299**	**[0.097]**
Natural gas	GDP	-0.713	[0.762]	1.157	[0.124]	0.778	[0.218]	**1.538**	**[0.062]**
Hydroelectricity	GDP	-2.335	[0.990]	-0.773	[0.780]	-1.351	[0.912]	-0.584	[0.720]
Energy	Human capital	0.364	[0.358]	0.592	[0.277]	0.932	[0.176]	0.078	[0.470]
Coal	Human capital	0.368	[0.357]	0.162	[0.436]	0.069	[0.473]	0.051	[0.480]
Oil	Human capital	0.824	[0.205]	0.992	[0.161]	0.555	[0.290]	-1.589	[0.944]
Natural gas	Human capital	-0.065	[0.526]	1.022	[0.153]	0.911	[0.181]	0.086	[0.466]
Hydroelectricity	Human capital	-0.818	[0.793]	-0.545	[0.707]	-3.490	[0.9998]	-0.922	[0.822]

Note: DW results are presented for the detrended first differences and VECM-filtered residuals. Each specification includes the full variable set, as either variables X and Y or as conditioning variables. The data are standardized by a normal transformation. The optimal number of lags is selected using the Schwarz information criterion and in all settings is equal to 1. Test statistics and corresponding p-values are reported in respective columns. Values in bold highlight the results significant at 10% level.

The nonlinear Granger causality test results show that there is no evidence that aggregate energy or any type of energy consumption Granger causes economic growth in China. However, economic growth is found to Granger cause oil consumption using either the detrended first difference or VECM residuals. Besides, no Granger causal relationship is observed between energy consumption and human capital using the DW test.

To compare the findings from the nonlinear Granger causality tests with those from the linear Granger causality test (Appendix Table A3), we summarize the conclusions on the directions of Granger causality for different energy measures and economic development as well as human capital in Table 5. As clearly shown, different conclusions are obtained from linear and nonlinear Granger causality tests. The linear Granger causal test results find no presence of Granger causal relationship between any type of energy consumption and economic development in China, while human capital seems to Granger cause aggregate energy use and coal consumption in the long run. The neutrality hypothesis is mostly supported by nonlinear Granger causality tests except for oil consumption which seems to fit the conservative hypothesis. However, Granger causality running from human capital to aggregate energy use and coal consumption does not appear in the nonlinear framework, suggesting that this finding is not robust and may be subject to a model bias.

Table 5: Granger causality test results

		Panel A: linear Granger causality				Panel B: nonlinear Granger causality			
		Raw data		VECM residuals		Detrended first difference		VECM residuals	
X	Y	X→Y	Y→X	X→Y	Y→X	X→Y	Y→X	X→Y	Y→X
Energy	GDP	-	-	-	-	-	-	-	*
Coal	GDP	-	-	-	-	-	-	-	-
Oil	GDP	-	-	-	-	-	*	-	*
Natural gas	GDP	-	-	-	-	-	-	-	*
Hydroelectricity	GDP	-	-	-	-	-	-	-	-
Energy	Human capital	-	*	-	-	-	-	-	-
Coal	Human capital	-	*	-	-	-		-	-
Oil	Human capital	-	-	-	-	-	-	-	-
Natural gas	Human capital	-	-	-	-	-	-	-	-
Hydroelectricity	Human capital	-	-	-	-	-		-	-

Note: Comparison between linear (Panel A) and nonlinear (Panel B) Granger causality results. Each specification includes the full variable set, as either variables X and Y or as conditioning variables. The optimal number of lags is selected using the Schwarz information criterion. For nonlinear tests the data are standardized by normal transformation. * indicates significance level at 10%.

This finding of neutrality between energy use and GDP is consistent with findings of Soytas and Sari (2006) and Yalta and Cakar (2012), but different from other studies using Granger-VECM tests (Yuan et al., 2008; Wang et al., 2011; Shahbaz et al., 2013) probably because of the uniqueness of incorporating human capital into the energy-augmented production function in this study. Our findings suggest that energy conservative policies are implementable and they are less likely to cause the economic slowdown in China. Furthermore, the causality running from human capital to the aggregate energy consumption and coal consumption found from the linear approach seems to indicate the substitution effect between human capital and energy/coal. However, it is not supported by the nonlinear Granger test.

4. Conclusions and policy implications

This study examines the causal relationship between energy consumption, human capital and economic growth in China during the period of 1965-2014. In addition to the standard linear Granger causal test using VEC model, we apply the recently developed nonlinear multivariate Granger causality test by Diks and Wolski (2015) to investigate the existence and directions of Granger causality relationships among the four variables. Both the aggregate and disaggregate energy consumption (coal, oil, natural gas, hydroelectricity) are examined. Results from both the linear and nonlinear Granger causality tests in general support the neutrality hypothesis that there are no causal link between energy and economic growth in China (except that GDP is found to Granger cause oil consumption in the DW test). The substitution effect between human capital and energy/coal is evidenced in the linear approach but no causal link between human capital and any type of energy use is identified by the nonlinear approach.

While there are two distinctive contributions to the energy-growth literature (namely, considering the role of human capital in the causal relationship between energy and economic development in China and the application of multivariate nonlinear Granger causality test of Diks and Wolski (2015)), this study has some limitations. First, this study considers only the supply-side approach; and the demand-side approach may provide more insights (Bloch et al., 2012; 2015). Second, we uses the national level data in China; and the regional heterogeneity in the energy consumption and resource distributions is not accounted for. Provincial or sectorial analysis using the same framework that incorporates the variable of human capital may be a promising extension in the future (Zhang and Xu, 2012; Herrerias et al., 2013).

There are some policy implications that can be drawn from this study. First, both the linear and nonlinear Granger causality test results imply that prudent energy conservation policy on any energy sector is feasible in China. Second, based on the weak evidence on the energy-human capital substitution effect found in the linear Granger test results, the government may take strategic measures to increase investment on the human capital associated with the research and development of new energy-efficient technologies so as to reduce the energy in particular coal consumption which has the most detrimental impact on environment.

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Appendix

Table A1: Summary of energy-growth nexus studies in China

Authors	Time period	Methodology	Variables	Causality
Energy-growth nexus				
Shiu and Lam (2004)	1971-2000	Johansen cointegration; Granger-VECM	Y, electricity	GDP ← E in the short and long run
Soytas and Sari (2006)	1971-2002	Toda-Yamamoto	Y,K,L,E	Neutrality
Yuan et al. (2007)	1978-2004	Johansen cointegration; Granger-VECM	Y, electricity	GDP ← E
Yuan et al. (2008)	1963-2005	Johansen cointegration; Granger-VECM	Y, K, L, E	GDP ↔ E in the long run, GDP → E in the short run; Electricity: GDP ↔ E in the long run, GDP ← E in the short run; Coal: GDP ↔ E in the long run; GDP → E in the short run; Oil: GDP ↔ E in both the short and long run
Wang et al. (2011)	1972-2006	ARDL, Granger-VECM	Y, K, L, E	GDP ← E in both the long run and short run
Akkemik et al. (2012)	1986-2008	Panel Granger causality	Y, E	Mixed results for provinces
Li and Leung (2012)	1985-2008	Panel cointegration, panel ECM	Y, coal	in the long run: GDP ↔ E for coastal and central region; GDP → E for western region
Yalta and Cakar (2012)	1971-2007	VAR, Meboot	Y, K, L, E	Neutrality
Zhang and Xu (2012)	1995-2008	Panel cointegration, panel ECM	Y, E, price	GDP → E
Zhang and Yang (2013)	1978-2009	Toda-Yamamoto	Y, K, L, E(coal, oil, gas)	GDP ↔ E
Shahbaz et al. (2013)	1971-2011	ARDL, Johansen cointegration, Granger-VECM	Y, E, financial development, K, international trade	GDP ← E
Herrerias et al. (2013)	1995-2009	Panel cointegration, panel FMOLS, panel DOLS (across regions)	Y, E(coal, electricity, oil, coke)	Total energy, Oil, coal: GDP → E in the long run Electricity, coke: GDP ↔ E in the long run Oil, coke: GDP → E in the short run Total energy, electricity, coal: GDP ↔ E in the short run
Bhattacharya et al. (2015)	1978-2010	ARDL, Toda–Yamamoto causality test	Y, coal, K, L, technology index	Coal → GDP
Energy-environment-growth nexus				
Zou and Chau (2006)	1953-2002	Johansen cointegration; Granger-VECM	Y, oil	GDP ↔ E in the long run; GDP ← E in the short run
Zhang and Cheng (2009)	1960-2007	Toda-Yamamoto	Y, CO_2, K, L (urban population), E	GDP → E in the long run
Chang (2010)	1981-2006	Johansen cointegration; Granger-VECM	Y, CO_2, crude oil, natural gas, coal, electricity	Oil, Coal: GDP → E Natural gas: Non causality Electricity: GDP ← E

Wang et al. (2011)	1995-2007	Panel cointegration, panel-VECM	Y, CO2, E	GDP ↔ E
Fei et al. (2011)	1985-2007	Panel cointegration, panel DOLS	Y, E, CO2	GDP ↔ E
Bloch et al. (2012)	1977-2008	Johansen cointegration; Granger-VECM	Y, K, L, coal, CO2	GDP ← E in both the short and long run (supply-side)
Lin and Moubarak (2014)	1977-2011	ARDL, Granger-VECM	Y, L, renewable energy, CO2	GDP ↔ renewable energy
Long et al. (2015)	1952-2012	Granger-VECM	Y, K, L, E(coal, oil, gas, electricity, hydro, nuclear), CO2	GDP ↔ coal, gas, electricity
Bloch et al. (2015)	1977-2013 (supply-side); 1965-2011 (demand-side)	ARDL, Granger-VECM	Y, K, L, E, coal, oil, renewable energy, CO2, price	GDP ↔ coal, oil, renewable energy

Note: This table summarizes the energy-growth nexus literature that investigates only China. Cross-country studies that includes China (for example Govindaraju and Tang, 2013; Cowan et al. 2014; and Bildirici and Bakirtas, 2014) are not included in the review. Relation X→Y (X←Y) means that the study found a significant relation from variable X onto Y (Y onto X), and X↔Y denotes a significant bidirectional relation between X and Y variables.

Table A2: Summary statistics of variables for 1965-2014

	Mean	S.D.	Min	Max
lnY	14.904	0.959	13.509	16.658
lnK	15.683	1.245	13.844	18.023
lnH	6.947	0.501	5.938	7.587
lnE	6.494	0.898	4.855	7.997
lnCoal	6.200	0.854	4.682	7.582
lnOil	4.761	1.003	2.394	6.254
lnGas	2.716	1.243	0.023	5.118
lnHydro	3.325	1.145	1.478	5.484

Table A3: Long-run and short-run linear Granger causality test

(a) For model with lnE

Dependent variables	Sources of causation								
	Short-run				Long-run				
	ΔlnGDP	ΔlnK	ΔlnH	ΔlnE	ECT	ECT GDP	ECT K	ECT H	ECT E
ΔlnGDP	-	6.993 [0.008]	28.005 [0.000]	1.743 [0.187]	17.901 [0.000]	-	1.425 [0.233]	4.580 [0.032]	0.104 [0.747]
ΔlnK	9.315 [0.002]	-	15.831 [0.000]	0.038 [0.846]	14.797 [0.000]	7.607 [0.006]	-	5.632 [0.018]	0.257 [0.612]
ΔlnH	0.022 [0.883]	0.014 [0.905]	-	0.639 [0.424]	0.087 [0.768]	0.026 [0.872]	0.003 [0.957]	-	0.629 [0.428]
ΔlnE	0.698 [0.403]	13.141 [0.000]	22.520 [0.000]	-	16.366 [0.000]	1.874 [0.171]	2.045 [0.153]	2.859 [0.091]	-

(b) For model with lnCoal

Dependent variables	Sources of causation								
	Short-run				Long-run				
	ΔlnGDP	ΔlnK	ΔlnH	ΔlnCoal	ECT	ECT GDP	ECT K	ECT H	ECT Coal
ΔlnGDP	-	5.865 [0.015]	28.653 [0.000]	1.750 [0.186]	18.460 [0.000]	-	2.130 [0.144]	5.137 [0.023]	0.661 [0.416]
ΔlnK	11.670 [0.001]	-	16.141 [0.000]	0.905 [0.341]	15.667 [0.000]	9.514 [0.002]	-	7.533 [0.006]	1.230 [0.267]
ΔlnH	0.004 [0.952]	0.023 [0.879]	-	0.184 [0.668]	0.106 [0.745]	0.002 [0.968]	0.006 [0.936]	-	0.186 [0.666]
ΔlnCoal	0.062 [0.803]	12.084 [0.001]	20.183 [0.000]	-	16.272 [0.000]	0.570 [0.450]	3.025 [0.082]	4.226 [0.040]	-

(c) For model with lnOil

Dependent variables	Sources of causation								
	Short-run				Long-run				
	ΔlnGDP	ΔlnK	ΔlnH	ΔlnOil	ECT	ECT GDP	ECT K	ECT H	ECT Oil
ΔlnGDP	-	9.098 [0.003]	16.722 [0.000]	0.009 [0.926]	13.172 [0.000]	-	4.162 [0.041]	6.925 [0.009]	1.146 [0.285]
ΔlnK	10.670 [0.001]	-	21.765 [0.000]	1.115 [0.291]	15.595 [0.000]	6.358 [0.012]	-	1.331 [0.249]	0.079 [0.778]
ΔlnH	0.000 [0.991]	0.128 [0.721]	-	1.819 [0.177]	0.242 [0.623]	0.001 [0.978]	0.057 [0.812]	-	1.715 [0.190]
ΔlnOil	0.254 [0.614]	2.902 [0.089]	2.578 [0.108]	-	3.667 [0.056]	0.414 [0.520]	1.296 [0.255]	0.831 [0.362]	-

(d) For model with lnGas

Dependent variables	Sources of causation								
	Short-run				Long-run				
	ΔlnGDP	ΔlnK	ΔlnH	ΔlnGas	ECT	ECT GDP	ECT K	ECT H	ECT Gas
ΔlnGDP	-	8.148 [0.004]	22.174 [0.000]	0.072 [0.788]	15.793 [0.000]	-	0.995 [0.319]	0.624 [0.430]	0.133 [0.715]
ΔlnK	11.096 [0.001]	-	20.870 [0.000]	1.968 [0.161]	14.323 [0.000]	6.169 [0.013]	-	2.002 [0.157]	0.357 [0.550]
ΔlnH	0.032 [0.859]	0.154 [0.695]	-	1.735 [0.188]	0.152 [0.696]	0.024 [0.876]	0.080 [0.777]	-	1.643 [0.200]
ΔlnGas	0.027 [0.869]	1.333 [0.248]	2.625 [0.105]	-	2.236 [0.135]	0.129 [0.719]	0.318 [0.573]	0.812 [0.368]	-

(e) For model with lnHydro

Dependent variables	Sources of causation								
	Short-run				Long-run				
	ΔlnGDP	ΔlnK	ΔlnH	ΔlnHydro	ECT	ECT GDP	ECT K	ECT H	ECT Hydro
ΔlnGDP	-	6.510 [0.011]	27.715 [0.000]	2.042 [0.153]	18.914 [0.000]	-	0.001 [0.974]	7.045 [0.008]	1.162 [0.281]
ΔlnK	12.733 [0.000]	-	17.011 [0.000]	0.383 [0.536]	14.657 [0.000]	8.534 [0.004]	-	7.759 [0.005]	0.233 [0.630]
ΔlnH	0.194 [0.660]	0.028 [0.868]	-	0.103 [0.748]	0.133 [0.715]	0.176 [0.675]	0.011 [0.917]	-	0.101 [0.750]
ΔlnHydro	0.162 [0.687]	3.885 [0.049]	1.349 [0.246]	-	0.785 [0.376]	0.206 [0.650]	3.084 [0.079]	0.889 [0.346]	-

Note: P-values in parentheses.