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Research Article

Modelling the Determinants of Coal Consumption in China

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Abstract: This study investigates the determinants of coal consumption in China, contributing to the ongoing debate on whether to replace coal or remain the dominant energy source. The study examines data extracted from different reliable sources including British Petroleum (BP), world Bank Data Indicator (WDI) and International Monetary Fund (IMF) ranging from 1985 to 2020. Autoregressive Distributed Lag (ARDL) model set was employed to estimate the short-term and long-term dynamics of the variables. Unit root tests were performed to assess the stability of variables, and Granger causality test was employed to investigate directional links. The findings revealed that GDP, Government Expenditure and Industrialization have a positive significant marginal relationship with Coal consumption in both the short and long run, whereas Crude Oil Prices and Domestic Credit have a negative impact on Coal Consumption. The analysis also reveals unidirectional causality flow of all considered variables from economic growth rates. The results suggest that coal and oil should remain the dominant energy sources in the Chinese economy to increase energy efficiency while recommending gradual investment and research in energy they are also renewed, with attention to population growth.

***Keywords*:** China, coal consumption, GDP, population, industrial development

JEL Codes: D16, Q11

1. Introduction

It is the role of the government to ensure that the demand for power or energy by its citizens and industrial sector is met; over the past decades, some of the authorities around the globe have invested hugely to ensure or maintain a level of power supply. Inputs are generally needed in the generation of energy; some of these inputs are raw materials or mineral deposits. It is however important to understand that some of these natural resources are not evenly distributed across the globe. While some parts of the world are rich, others are poor. This, however, affects a country's ability to produce a stable level of power supply. Natural gas, coal, hydropower, solar power, and thermal energy are the primary inputs for the generation of energy or power in many countries. In the case of China (National Bureau of Statistics, 2019), amongst these inputs, coal accounts for about 70% of consumption and about 77% of the generation of electricity. This is amazing because while some countries consider coal a traditional means of generating power, China sees it as its main energy supply. Within the framework of coal consumption, there has been a significant amount of research recorded in this area: Cattaneo et al. (2011); Du et al. (2012); Ma and Oxley (2012); Hao et al. (2015); Li and Leung (2012). Some of these researchers investigated the relationship between coal consumption and economic growth in China or how urban population will affect coal consumption; the outcomes were almost similar and will be reviewed

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in the literature section. However, even though it can be said that coal consumption is a vital driver of economic growth, the process involved in the production of energy from coal contributes to negative externalities in some economies, including China (Figure 1).

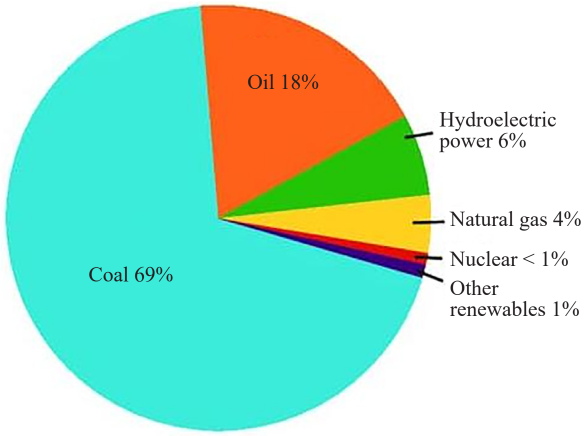

Figure 1. Global energy consumption
Source: EIA stats USA

Even though there has been an overall increase in the consumption of coal in China, in 2014 and 2015, coal consumption in China continued to decline. China's coal consumption fell to 4.42 billion tons, down 2.9 percent from 2014 and 3.6 percent from 3.963 million tons in 2015. Given the annual growth rate of 8.3% from 2004 to 2013 or the annual growth rate of 12% from 2000 to 2013, the sharp decline in coal consumption between 2014 and 2015 has significant implications for domestic and global climate change policy, to put it cautiously. Study research should be accepted (Figure 2).

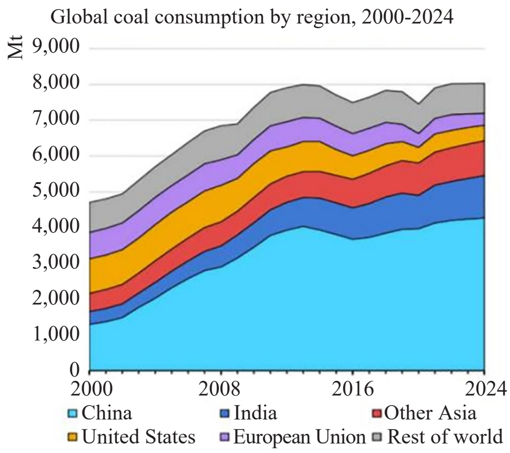

Figure 2. Global coal consumption
Source: IEA 2021 coal report

Research on coal consumption and pricing is vital, as many see the power supply as an indicator of growth. Even though this research adds to existing literature, it will provide a vivid picture of the coal market in China, what factors investors or new firms must take into consideration before making attempts to invest in the coal sector in China, and what necessary change is needed for the coal sector of China or policy changes in the supply of power. Even though this research answers the question of whether the economy of China should adopt more recent or new means of energy, it should be noted that this study is significant to two main groups: the government of China (that is, to know how growth changes as coal consumption changes) and as literature for or a springboard for another research.

Focusing on the determinants of coal consumption in China, this study makes a unique contribution to energy economics through a comprehensive analysis of factors affecting coal consumption over a 35-year period (1985-2020). in the 19th century. Using an autoregressive model of estimation that incorporates economic growth and government spending, the study captures short- and long-term trends, providing nuanced insights into the complex interactions affecting coal transport plays a role in the world's largest consumer of coal, making it a valuable addition to the ongoing energy policy debate. Understanding the determinants of coal consumption in China is important due to the country's dominant position in the global energy market and its significant impact on environmental health. As the largest consumer of coal in the world, China's electricity guidelines and charcoal consumption model have methods to explore policy implications for important insights for grassland and enable alternative charcoal consumption. While addressing nationwide and global concerns to help expand strategies for equitable management, balancing, and trading of energy inputs, the research contributes most effectively to a deeper understanding of China's energy development but additionally supports aspects of informed, sustainable electricity direction that can serve as a model for a coal-fired economy. To achieve the goals, the research is structured into five main parts: an introduction, a review of other findings, data methods, empirical findings, and a conclusion.

2. Literature review

The relationship between energy levels and income, and the strong relationship between coal consumption and economic growth, is contradictory. Since Kraft (1978) worked on the interrelated supply of electricity and industrial development, much research has been conducted in this field. The wide scope of experimental applications, and the causal relationship of electricity consumption to industrial growth in China, have been valued by researchers. The relationship between finance and business growth is significant, irrespective of the direction of causality. Some authors, such as Apergis and Payne, 2010, have treated coal as a crucial factor of production and have also claimed that if causality runs from energy saving to reduced greenhouse gas emissions, it may have implications of monumental proportions for business growth. In the study in 2008, Jinke and Dianming determined the relation between GDP and coal consumption in China and Japan but could not establish causal factors in India, South Korea, and South Africa.

Michiekaa and Fletcher (2012) examined the relationship between coal consumption, urban population, and GDP in China by applying Vector Auto-Regression, Granger causality, and Variance Decomposition methods. The results proved that a causality exists between GDP and coal consumption. According to the variance decomposition report, it is the urban population and coal that cause electricity production. Burke and Liao (2015) estimated the price elasticity of demand for coal in China by applying price elasticity of demand methods in their study. In their finding, the estimated elasticities range from -0.3 to -0.7, proving provincial coal demand elasticity in 2012.

According to Bloch et al. (2012), the study aimed at ascertaining the relationship between income and coal consumption in China. The model used for this study was Cointegration and Vector Error Correction Models. The results showed that while there is a one-way causality from coal consumption towards its production, there exists one-way causality from income towards coal consumption in both the short and the long run. Chai et al. (2019) decomposed the driving forces and analyzed future trends in coal consumption using the LMDI Decomposition method in China. They forecast that the quantity of coal consumed would decrease by an annual average of 0.4% from the year 2017 to 2030.

Bloch et al. (2015) estimated the relationship that existed between the main industrial GDP of China and the consumption of different raw materials, which involves coal, oil, and renewable energy, by using Auto Regression Distributed Lag and Vector Estimation Correction models. The mentioned sources of energy drove the economic growth of China to a significant extent. Also, Fu et al. (2020) examined the time shift of coal prices concerning clean energy reserves in China with the help of the VAR-DCC-GARCH approach, and significant bidirectional volatility spreading has been found between the coal market and unattractive energy supply.

Yuan et al. (2010) try to analyze the relationship of energy prices and energy consumption through Cointegration, Variance Decomposition, and Impulse Response methods in China. They found that in case of an increase of energy prices, it would not result in falling economic output; however, it would mean a decrease in energy consumption. Henryk and Łukasz (2011) used the Nonlinear Granger causality test to check for causality in the quarterly coal consumption data for Poland's economy and found it to be neutral to economic growth.

Li and Leung (2012) examined the coal consumption-real GDP nexus of China with modern panel techniques. The authors found that there is bidirectional causality between coal consumption and GDP in coastal and central regions of China. Also, Wolde-Rufael, 2010 try to use cause-effect relationship in coal consumption and real GDP in China, Japan, Korea, USA, South Africa, and India using VAR, Granger causality test, and Toda and Yamamoto. They found that one-way causality exists with coal consumption as the cause of economic growth for India and Japan, whereas it goes in reverse in the cases of China and South Korea.

According to IEA, global coal demand in 2023 continues to surge on the back of China and India. Also, in China, coal consumption increased 4.6% amid rising demand for electricity coupled with low hydropower output. The IEA projects that Chinese coal consumption will slightly decline and subsequently plateau through 2026. Kao et al. (2023) characterize the spatial and temporal nature of coal consumption and associated carbon emissions in China. Effective carbon tax policies should be executed in order to reduce these emissions while keeping track of economic growth.

CoalNewswire (2023) reports that in 2023, China's coal consumption surged, largely impelled by factors like economic growth, industrial demand, and energy security policies. Also, Global Energy Monitor, 2024 reports that in China, coal capacity construction started to increase to an eight-year high in 2023, while global trends saw a decline.

The Coal Hub (2023) reports that China's domestic production surged to 4.66 billion tons in 2023, with imports also increasing significantly. Additionally, Environmental Science and Pollution Research (2023) points out the spatial and temporal characteristics of coal consumption and carbon emissions in China.

The Coal Trader keenly details China's surge in coal consumption in 2023 and the implications this would have on the environment. S&P Global Commodity Insights (2024) reports that coal made up nearly 60% of China's electricity supply in 2023, while coal-fired power supply is increasing to cover hydropower shortages. Finally, Global Energy Monitor (2024) announced that China's coal imports were headed for a record year in 2023, due to steps taken to ensure adequate supplies amid developing El Niño conditions.

3. Data and methodology

3.1 *Data*

In Table 1 the research uses a secondary annual dataset from different reliable sources including British Petroleum (BP), world Bank Data Indicator (WDI) and International Monetary Fund (IMF) with observations spanning over three decades (1985-2020). The researcher adopted several robust methodologies to analyse the factors influencing coal consumption in China. Autoregressive Distributed Lag (ARDL) model set was employed, which is more reliable for examining both short-term and long-term dynamics between variables. This method enables the inclusion of integrating variables at different orders, providing flexibility and robustness in the analysis. The study also employed unit root tests to aware the level of stationarity of the variables, ensuring the reliability of the regression results. Additionally, Granger causality test was utilized to explore the directional relationships among the variables, identifying potential causative influences between coal consumption and regressors such as GDP growth, inflation, urbanization, industrialization, oil prices, financial development, and government spending. This extensive methodological framework guarantees a thorough evaluation of the determinants of coal consumption in China.

These variables were chosen based on the theoretical foundation and existing literature (Michiekaa & Fletcher, 2012). In his estimation, he used coal consumption, GDP, and urban population (Burke & Lao, 2015). Also, Figure 3 shows the time series graph of the variables.

Table 1. Variable summary

Variable type	Variables	Source
Dependent variable	Coal consumption (COALC)	BP
Independent variable	Gross domestic product annual growth (GDPG)	WDI
Independent variable	Inflation (INFL)	IMF
Independent variable	Electricity generated from coal (EGFC)	BP
Independent variable	Urban population annual growth (UPAG)	WDI
Independent variable	Industrialization (INDST)	WDI
Independent variable	World crude oil prices (LWOP)	BP
Independent variable	Domestic credit to provided sector (DCTPS)	WDI
Independent variable	General government spending (GOVE)	IMF

Source: Author's estimation

A descriptive analysis is performed on the collected data. It provides the metrics of central tendency, dispersion, and normality. A metric of central tendency is the mean, which represents the average value of a dataset. It is calculated by adding up all the values in the dataset and then dividing the total number of values. The standard deviation measures the average deviation of each item in a dataset from the mean, helping to detect outliers and describe value ranges, with higher values indicating wider variability and lower values indicating closer clustering around the mean. Skewness is a distribution metric that measures asymmetry. Unlike a negatively skewed distribution, which has a tail that extends to the left and a large fraction of values associated with the top and right, a positively skewed distribution has a tail that extends to the right.

Kurtosis measures the rotation of the tail in a probability distribution from a normal distribution, where positive kurtosis indicates more tails and sharper peaks, and negative kurtosis indicates lighter tails and thinner peaks.

Table 2. Descriptive statistics

	COALC	GDPG	INFLA	INDTS	URBAN	DCTPS
Mean	13513.13	9.220626	5.129444	44.12364	3.682902	112.7812
Maximum	22911.17	14.23086	24.10000	47.55740	4.601685	182.8681
Minimum	4736.265	2.239702	-1.400000	37.84283	2.078140	66.19227
Std. Dev.	7080.971	2.856572	6.117403	2.734732	0.695565	29.00366
Skewness	0.229650	-0.188276	1.609076	-0.734628	-0.616208	0.510126
Kurtosis	1.304063	2.891699	4.804446	2.413684	2.309508	2.530431
Jarque-bera	4.630737	0.230280	20.41878	3.753718	2.993440	1.892114
Probability	0.098730	0.891241	0.000037	0.153070	0.223863	0.388269
Observations	36	36	36	36	36	36

Source: Author's estimation

Table 2 reveals how the variables are described statistically, with an average of 13,513.13 TWh of coal consumption witnessing overall significant growth, registering a minimum of 4,736.265 TWh and a maximum of 22,911.17 TWh over the past three decades. This implies that over the period of observation, the variable DCTPS is more complex to predict as compared to the others. On the asymmetry and normality aspects of the description, based on the probability value of the Jarque Bera Stats, all variables except the price of coal are reported to be normally distributed in series.

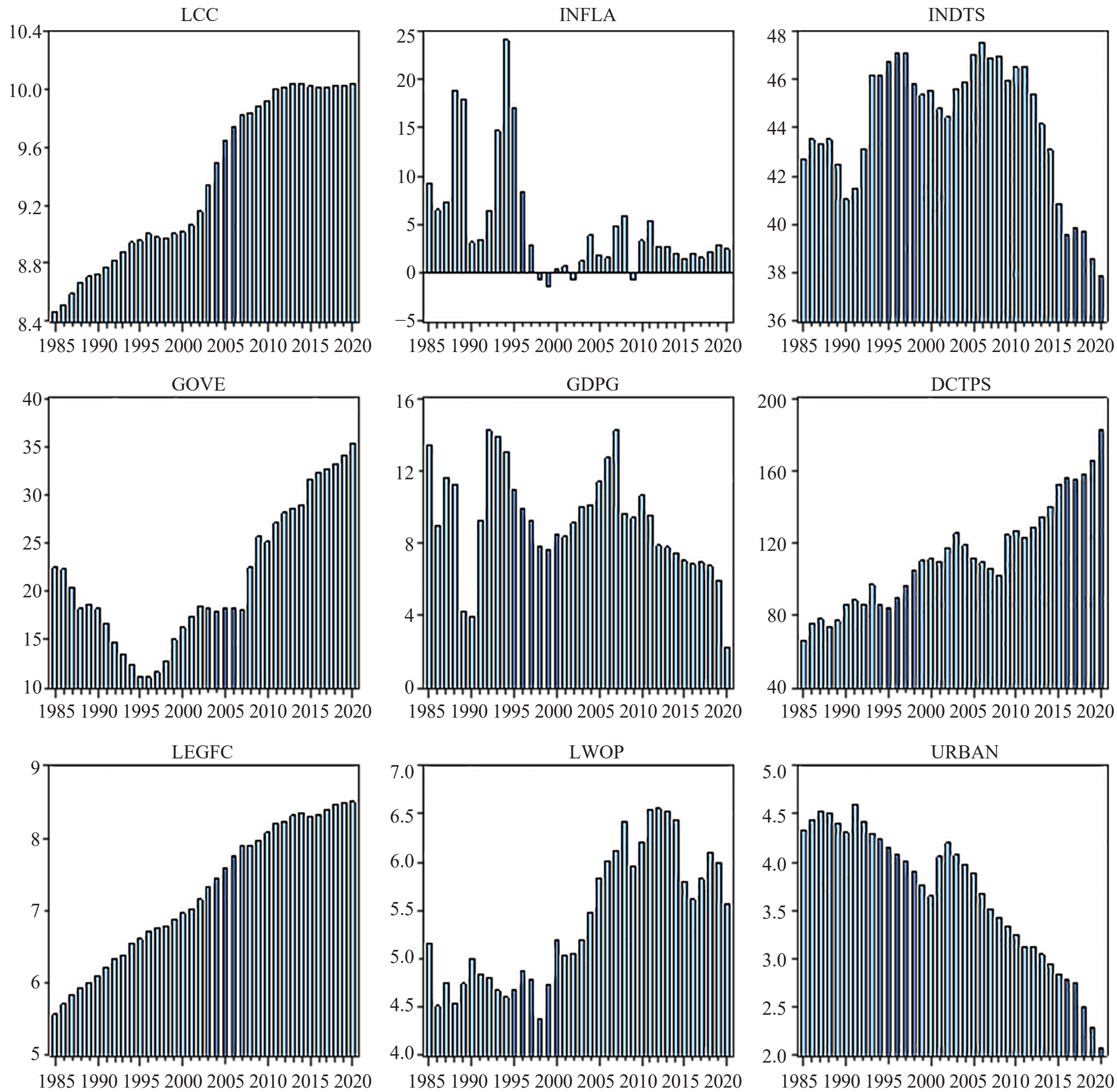

Figure 3. Time series graphs

Source: Author's estimation

3.2 *Model specification*

Model specification involves the selection of appropriate variables and functions to accurately represent relationships between independent dependent variables in a mathematical model This includes deciding which variables to include or exclude, decisions on how to control potential interactions, and the choice of linear and nonlinear forms. Appropriate model specification is essential for unbiased, consistent, and efficient estimation, which ensures validity and reliability of model findings.

3.2.1 *Stationary test or unit root test*

If the mean and variance of a set of data remain constant throughout time and the covariance value between two time periods depends only on the interval or lag between the two time periods rather than the time at which the covariance is computed, the data is said to be stationary. To avoid spurious regression results it is very vital to test the stationarity of the series. To test for the unit root, we use the augmented dickey fuller tabulated by Fuller (1979) with specifications as follows.

$$Y_t = \beta Y_{t-1} + \mu_t \tag{1}$$

If $\beta = 1$ it means, there is a unit root problem, or the series is not stationary but if $\beta < 1$ we can conclude the series is stationary. In the above equation, we cannot directly test the hypothesis that $\beta = 1$ with the use of T-test because this will be biased. So, we subtract Yt-1 from both sides of the equation

$$Y_t - Y_{t-1} = \beta Y_{t-1} - Y_{t-1} + \mu_t = (\beta - 1)Y_{t-1} + \mu_t \tag{2}$$

$$\Delta Y = \theta Y_{t-1} + \mu_t \tag{3}$$

Where θ is the same as $(\beta - 1)$ so for each time series the hypothesis is:
H0: $\theta = 0$ (that is there is unit root, or the time series is not stationary or has a stochastic trend)
H1: $\theta < 0$ (that is there is NO unit root, or the time series is stationary or has NO stochastic trend)
The ADF is also efficient because it allows for serially correlated error term μt

$$\Delta Y = \beta_1 + \beta_{2t} + \theta Y_{t-1} + \Sigma \alpha i \Delta Y_{t-1} + \mu_t \tag{4}$$

Several unit root tests were created by Phillips and Perron in 1988, and they have since gained popularity in the study of financial time series. The primary areas where the Phillips-Perron (PP) unit root tests and ADF tests diverge are in their approaches to serial correlation and heteroskedasticity in the errors. The PP tests specifically ignore any serial correlation in the test regression while the ADF tests use a parametric autoregression to approximate the ARMA structure of the errors in the test regression. The PP tests' test regression is

$$\Delta Y_t = \beta_0 X_t + \pi Y_{t-1} + U_t \tag{5}$$

Where μt is heteroskedastic and $I(0)$. Any serial correlation and heteroskedasticity in the test regression's errors are considered by the PP tests.

3.2.2 *Cointegration test and lag length*

When two or more series are non-stationary, but their linear combination is stationary, cointegration takes place. Testing for cointegration is necessary to ascertain whether one is modeling an empirically significant relationship. In this analysis, the long-term associations between the variables are examined. First, using the Akaike criteria (AIC), Schwarz Bayesian criterion (BIC), Hannah-Quinn criterion (HQC), and Akaike's Final Prediction Error (FPE) criterion, the appropriate number of lag lengths must be determined. While the AIC and FPE operate best with smaller datasets (under 60 observations) and are the least likely to result in an underestimate, the HQC frequently performs better with larger datasets (over 120 observations) (Liew, 2004). We can choose the lag length depending on which criterion result appears most frequently, and if there are ties, we can choose the lag length that is most suited for our model, presuming that too few or too many lags may not effectively depict the extent of the link between variables.

After ensuring the presence and absence of unit root in the time series analysis, it is vital to ensure that variables have long run or short run relationships or equilibrium relationships.

$$Yt = \beta 1 + \beta 2Xt + \mu t \tag{6}$$

Where Y and X are integrated at order 1, suppose we now subject the error term to unit root testing.

$$\mu t = Yt - \beta 1 - \beta 2Xt \tag{7}$$

And discover that the error term is integrated that order (0) then it can be said there is cointegration within variable. $\beta 2$ is the cointegration parameter and it is said that if variables are set to be co integrated, then they can be used and interpreted for long run analysis. In establishing causality, we must make sure that the underlying variables are stationary. It is important to note that

3.2.3 *Auto regressive distribution lag (ARDL)*

This model contains lagged values of the dependent variable as an explanatory variable together with the current and lagged values of the regressors. Unlike VAR model, which is mainly designed for endogenous variables, the ARDL model is designed for both exogenous and endogenous variables. This model is best and should used in the case when variables are integrated and order 0 and 1 only. Supposed variables are integrated at seconds, using this model will portray spurious results. From the results of the bound test, we can decide whether to specify for the long and short run regression. If variables are cointegration, then it is approved to run the long run ARDL which is the same as the error correction model. One of the advantages of the ARDL model is that results obtained are said to be unbiased. The model is generally specified as

$$Yt = Yo\iota + \sum_{\iota=1}^{P} \delta Yt - 1 + \sum_{\iota=0}^{q} \beta\iota Xt - 1 + E\iota t \tag{8}$$

Y and X are dependent and explanatory variables respectively integrated at $I(0)$ or $I(1)$, δ and β are the coeffiecients, p, q is the optimal lag order and Eit is the error term which is serially uncorrelated. With respect to our variables, we specify for the bound test as

$$\Delta LCC\tau = \alpha o\iota + b1LCC\tau - \iota + b2GDPG\tau - \iota + b3LWOP\tau - \iota + b4\ INDTS\ \tau - \iota + b5INFL\tau -$$

$$\iota + b6DCPTS\tau - \iota + b7LEGFC\tau - \iota + b8GOVE\tau - \iota + b9\ URBA\ \tau - \iota \sum_{\iota=1}^{P} \alpha 1\iota \Delta LCC\tau - 1 +$$

$$\sum_{\iota=1}^{q} \alpha 2\iota \Delta GDPG\tau - 1 + \sum_{\iota=1}^{q} \alpha 3\iota \Delta LWOP\tau - 1 + \sum_{\iota=1}^{q} \alpha 4\iota \Delta\ INDTS\ \tau - 1 + \sum_{\iota=1}^{q} \alpha 5\iota \Delta\ INFL\ \tau -$$

$$1 + \sum_{\iota=1}^{q} \alpha 6\iota \Delta DCPTS\tau - 1 + \sum_{\iota=1}^{q} \alpha 7\iota \Delta\ EGFC\ \tau - 1 + \sum_{\iota=1}^{q} \alpha 8\iota \Delta\ GOVE\ \tau - 1 + \sum_{\iota=1}^{q} \alpha 9\iota \Delta URBA\tau - 1 \tag{9}$$

If no Cointegration the short run model can be specified as

$$\Delta LCC\tau = \sum_{\iota=1}^{P} \alpha 1\iota \Delta LCC\tau - 1 + \sum_{\iota=1}^{q} \alpha 2\iota \Delta GDPG\tau - 1 + \sum_{\iota=1}^{q} \alpha 3\iota \Delta LWOP\tau - 1 +$$

$$\sum_{\iota=1}^{q} \alpha 4\iota \Delta \ INDTS \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 5\iota \Delta \ INFL \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 6\iota \Delta \ DCPTS \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 7\iota \Delta \ EGFC \ \tau -$$

$$1 + \sum_{\iota=1}^{q} \alpha 8\iota \Delta \ GOVE \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 9\iota \Delta \ URBA \ \tau - 1 + \ Ett \tag{10}$$

If there is Cointegration, we can specify as follow adding the error correction model in it

$$\Delta LCC\tau = \sum_{\iota=1}^{P} \alpha 1\iota \Delta LCC\tau - 1 + \sum_{\iota=1}^{q} \alpha 2\iota \Delta GDPG\tau - 1 + \sum_{\iota=1}^{q} \alpha 3\iota \Delta LWOP\tau - 1 +$$

$$\sum_{\iota=1}^{q} \alpha 4\iota \Delta \ INDTS \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 5\iota \Delta \ INFL \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 6\iota \Delta \ DCPTS \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 7\iota \Delta \ EGFC \ \tau -$$

$$1 + \sum_{\iota=1}^{q} \alpha 8\iota \Delta \ GOVE \ \tau - 1 + \sum_{\iota=1}^{q} \alpha 9\iota \Delta \ URBA \ \tau - 1 + \lambda ECT\tau - 1 \tag{11}$$

3.2.4 *Models*

$$LCC = GPDPG + LWOP + INDTS + INFL + DCTPS + EGFC + GOVE + URBA \tag{12}$$

$$LEINT = \alpha o + \beta 1 \ GPDPG \ + \beta 2 \ LWOP \ + \beta 3 \ INDTS \ + \beta 4 \ INFL$$

$$+ \beta 5 \ DCTPS \ + \beta 6 \ EGFC \ + \beta 7 GOVE + \beta 8 URBA \tag{13}$$

Equations 12 and 13 represent the economic model and econometric model, respectively. The difference between these two models is that the econometric has the constant and trend parameters. The trend is also called the coefficient; in equation 13, we have 5 coefficients (from $\beta 1$to $\beta 5$), each of these coefficients explains how much the dependent variable will change if the explanatory variable increases by 1 unit or a percentage. While the other four variables are regressors, the log value of the log of coal consumption remains constant.

4. Results and discussion

4.1 *Unit root*

Before performing the stationary test, the log form of variables was taken. To test whether our variables are stationary (UNIT ROOT) or not, we employ the Augmented Dickey-Fuller and KPSS unit root tests and will reject or accept the null at 5% significance.

Table 3. ADF unit root test

Variables	Levels	Prob. value	1st. diff	Prob. value
LCC	-1.288283	0.6236	-2.672853	0.0898
DCTPS	0.531383	0.9855	-5.012788	0.0003***
GDPG	-2.258571	0.1905	-5.073205	0.0002***
GOVE	1.133388	0.9970	-3.338977	0.0208***
INDST	0.089173	0.9603	-3.676999	0.0091***
INFL	-4.430943	0.0065**		
LEGFC	-1.889149	0.3332	-3.839177	0.0060***
LWOP	-3.661999	0.0430**		
URBA	1.633608	0.9993	-4.620160	0.0008***

Source: Author's estimation

Table 4. KPSS unit root test

Variable	KPSS stats	5% Critical value
LCC	0.153267*** $I(1)$	0.463000
DCTPS	0.221114*** $I(1)$	0.463000
GDPG	0.335996*** $I(0)$	0.463000
GOVE	0.115987** $I(1)$	0.146000
INDST	0.232001*** $I(1)$	0.463000
LEGFC	0.378545*** $I(1)$	0.463000
LWOP	0.106588** $I(0)$	0.146000
URBAN	0.390668*** $I(1)$	0.463000

Source: Author's estimation

The outcome shows that all variables have unit root problems except inflation and the log of world oil prices (Tables 3 and 4). This means that apart from inflation and oil prices, all the other variables are stationary in different orders of integration. The series log of coal consumption was observed to be integrated at first order, but at the 10% level of significance, to ensure uniformity of integration orders, we employed the KPSS unit root to check if it was possible for the series log of coal consumption to be stationary at first order. The result from the KPSS confirms the mixture of $I(1)$ and $I(0)$ orders of integration, setting the basis for the use of the auto-distributed lag model as a method of estimation.

4.2 *Cointegration (ARDL bound test)*

To show that the variables have a long-run relationship, we run an ARDL model based on the unit root test.

To see if there is a long-run relationship between subjectivity and extrinsic variables, the general rule states that if the F-stat (14.56487) is greater than all significant levels of integration, then the null hypothesis of any relationship should not be accepted. Thus, it is possible to confirm that the pertinent variables have been integrated (see Table 5).

Table 5. Bound test

Test Statistic	Value	Signif.	*I*(0)	*I*(1)
F-statistic	14.56487	10%	1.85	2.85
k	8	5%	2.11	3.15
		2.5%	2.33	3.42

Source: Author's estimation

4.3 *Lag selection*

The most important question to be answered here is, why lag selection? It is important to note that the effect of the regressor on the explained variable is hardly instantaneous or does not act immediately. This effect happens over a period; this lapse of time is what we tend to consider the lag values of variables or series.

Table 6. Lag selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-406.2386	NA	0.327934	24.42580	24.82984	24.56359
1	-47.74479	506.1089	3.14e-08	8.102635	12.14300	9.480515
2	104.8002	134.5985*	1.46e-09*	3.894106*	11.57080*	6.512079*

Source: Author's estimation

In this analysis, the long-term associations between the variables are examined. First, using the Akaike criteria (AIC), Schwarz Bayesian criterion (BIC), Hannah-Quinn criterion (HQC), and Akaike's Final Prediction Error (FPE) criterion, the appropriate number of lag lengths must be determined. AIC and FPE operate best with smaller datasets (under 60 observations) and are the least likely to result in an underestimate, the HQC frequently performs better with larger datasets. We can choose the lag length depending on which criterion result appears most frequently, and if there are ties, we can choose the lag length that is most suited for our model, presuming that too few or too many lags may not effectively depict the extent of the link between variables (Table 6).

4.4 *ARDL results*

The short run estimate as seen in Table 7 shows a significant negative relationship between DCPTS and LCC, that is domestic credit provided to private sector has a negative association with the coal consumptions levels in the economy of China. In magnitude the estimate claims that over the observed period a 1% increase in domestic credit will result to a 0.001% fall in coal consumption levels ceteris paribus. In a real economic sense this outcome can be backed with the argument that the rate at which private individuals collect loans does not mean a significant amount is spent on the consumption of coal, it explains that private individual will tend to spend collected loans on long-term financial investment to yield greater profits. So, financial development is not a good determinants of the coal consumption levels in the chinless economy. The short run results confirm a significant negative relationship between INFL and LCC, that is the rate of inflation, has a negative association with the coal consumption levels in the economy of China. In magnitude the estimate claims that over the observed time period a 1% increase in inflation will result in a 0.003% fall in coal consumption levels ceteris paribus. In real economic perspective, this makes great sense this outcome can be backed by the argument relating to the traditional effect of an increase in prices levels on goods or services. The rate at which the general level of price increase means a significant amount purchased on the consumption of coal will fall. In contrast, the short run results confirm a significant negative relationship between URBAN and LCC, that is the rate of Urbanization, has a negative association with the coal consumption levels in the economy of China. In magnitude the estimate claims that over the observed time a 1% increase in the growth rate of urban population will result in a 0.001% fall in coal consumption levels ceteris paribus. The magnitude of effect is as the same as that of domestic credit. With reference to the factors that tend to affect demand, we understand population plays a vital and positive role, but in view of our estimate we observe that as the urban area continues to witness a significant amount of growth coal consumption levels will fall. This means coal consumption will no longer enhance the growth of population and people in the urban areas will tend to use other modern energy in their houses such hydroelectricity consumption. The result between URBAN and LCC is not in line with that of (Balmer, 2007)

Table 7. ARDL short run

Variable	Coefficient	Std. error	*t*-Statistic	Prob.
D (LCC (-1))	0.495162	0.046529	10.64200	0.0000
D (DCTPS)	-0.001480	0.000394	-3.753292	0.0038
D (GOVE)	0.012040	0.001265	9.516529	0.0000
D (GOVE (-1))	-0.012940	0.001344	-9.624246	0.0000
D (INDTS)	0.016030	0.001763	9.093897	0.0000
D (INDTS (-1))	-0.007559	0.001673	-4.518536	0.0011
D (INFLA)	-0.002971	0.000447	-6.653927	0.0001
D (INFLA (-1))	0.000650	0.000306	2.127749	0.0592
D (LEGFC)	0.813125	0.035045	23.20256	0.0000
D (LEGFC (-1))	-0.263582	0.034333	-7.677215	0.0000
D (LWOP)	-0.075396	0.009458	-7.971784	0.0000
D (LWOP (-1))	-0.030274	0.005609	-5.397504	0.0003
D (URBAN)	-0.000905	0.012134	-0.074562	0.9420
D (URBAN (-1))	-0.234804	0.018272	-12.85020	0.0000
ECT (-1) *	-0.717362	0.043123	-16.63528	0.0000

Source: Author's estimation

The short run results confirm a significant negative relationship between LWOP and LCC, that is the oil prices, have a negative association with the coal consumption levels in the economy of China. In magnitude the estimate claims that over the observed period a 1% increase in the Log of oil prices will result to a 0.08% fall in coal consumption levels ceteris paribus. At this level of our analysis, the magnitude of effect is far greater as that of domestic credit inflation and urbanization. With reference to the factors that tend to affect demand, we understand price of other goods plays a vital role, but in view of our estimate we observe that as the price of oil increases, we will witness a significant amount of growth coal consumption levels will fall. This means coal and oil are considered as complementary consumption when energy generation in the economy of China is concerned. To individual, both commodities could be considered as perfect substitute, but if the general economy of China is concerned both coal and oil are using same times to enhance the supply of energy. On the bright side of our estimation, we confirm that GOVE, INDST and LCC have a short run and positive association. Government expenditure together with the levels of industrialization will help to boost the levels of coal consumption in the economy of China. In magnitude, ceteris paribus, coal increases by 0.01% and 0.02%

for a % increase in government expenditure and industrial development respectively. Based on the economic concept of derived demand, we confirm that electricity generated from coal is significantly positively related to coal consumption levels.

In the long term (Table 8) we confirm that GOVE, INDST, GDPG, and LEGFC have a long run and positive association with LCC. Government expenditure together with the levels of industrialization will help to boost the levels of coal consumption in the economy of China. In magnitude, ceteris paribus, coal increases by 0.02% and 0.01% for a % increase in government expenditure and industrial development respectively. The results from the relationship between industrial development and coal consumption further imply that in the long term the positive impact will fall by a smaller amount this is consistent (Tang et al., 2018). There is a positive link between coal consumption and economic development. In a microeconomic sense we relate our argument to that of the income effect. From the result, we observe that an increase in the rate of national income will increase coal consumption, so we term coal as a normal good. In magnitude the outcome claims that coal consumption will improve by 0.004% if income increases by a % ceteris paribus. The positive relation between income and coal consumption the general economy sense is in line with the work of Bloch et al. (2015). We are limited to comparing the results of electricity generated from coal, financial development and oil prices because our research is amongst the few that tends to address and explain how much these factors will tend to influence the consumption levels of coal in China.

Table 8. Long run ARDL

Variable	Coefficient	Std. error	*t*-Statistic	Prob.
DCTPS	-0.004449	0.001224	-3.636034	0.0046
GDPG	0.004474	0.003432	1.303542	0.2216
GOVE	0.024924	0.003279	7.600992	0.0000
INDTS	0.010779	0.004931	2.185786	0.0537
INFLA	-0.001854	0.001469	-1.262085	0.2356
LEGFC	0.693685	0.041739	16.61950	0.0000
LWOP	-0.019310	0.029374	-0.657395	0.5258
URBAN	0.168745	0.042840	3.938981	0.0028
C	3.240384	0.420290	7.709877	0.0000

Source: Author's estimation

4.5 *Diagnostic test*

A good regression analysis must be free of autocorrelation or serial correlation, or heteroskedasticity, which means that variables must be homoscedastic, with evenly distributed errors, whether they follow a normal distribution, linear, and stable model variables, according to the multiple regression assumptions. The relationship between the explained and the explanatory variables must be perceived and given by a linear parameter or coefficient, according to the idea of linearity or the assumption of linearity, which states that the equation or model most likely contains linear parameters. Second, the conditional mean, which represents the expected value of a regressor, should be zero, and the error term should also be zero. For variables to be homoscedastic, we mean the variance of the error term with respect to the regressor must be fixed. Table 9 shows the results of several tests done to determine the model's robustness. Ramsey reset test results for confidence level show that the model is well-defined, unique, independent of correlation, and well-distributed. Iterative analysis is used to determine the stability of the sequence structure. As shown in Figure 4, the results of the CUSUM tests are within 5% of significance, indicating a strong model.

Table 9. Diagnostic test

Test	F/T stats	Prob. value
Breusch-godfrey serial correlation LM test	3.483922	0.1128
Heteroskedasticity test: Breusch-pagan-godfrey	1.641425	0.2570
Ramsey RESET test	0.112845	0.7484
Normality test	0.497999	0.7799

Source: Author's estimation

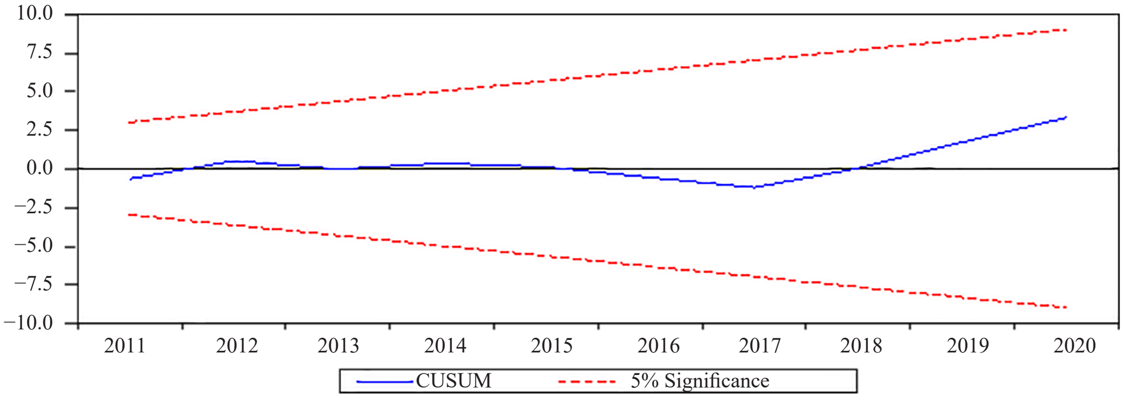

Figure 4. CUSUM test

Source: Authors' finding

4.6 *Impulse response*

The change of the variable of interest to us over time after injury at a specific moment is described by the impulse response function. This section of the research tells us what innovation will occur to LCC if there is a 1 or 2 standard deviation shock. From shocks, the regressor affects the explained variables. For this case, we can say that price is the one vital aspect that will lead to the shock of coal consumption, so our goal here is to represent the situation when this shock happens. To fully understand the dynamic relationship between the responses of the determinants of coal consumption, we conclude our analysis by evaluating impact response functions. It describes the evolution of a dependent variable over a period after a shock at a given time. Following this sequence, the authors evaluate shock-IRFs as explained by James (1994) based on Cholesky's decomposition. From Figure 5, we observe the response of coal consumption because of shocks from inflation, industrial, economic, and financial growth over 10 years. LCC will have a slight downward trend response to itself. This means that if there is a shock to the coal consumption of China, the response will be a downward trend beginning from the positive side of the graph. Similar responses are observed in the shock placed on coal consumption by the energy generated by coal. A typical downward and upward trend movement is equally observed in the response of shocks from urban population growth to coal consumption and shocks from economic growth to coal consumption. This haphazard trend from GDPG shocks to LCC does not cross the negative line. This implies that the deviation from GDPG will make slight positive changes but not any negative response to coal consumption in China. The movement along and across the positive and negative sides of the impulse response graph is observed in the shock response from inflation to coal consumption. This implies that over the predicted number of years, inflationary shocks will be both a positive and negative response to coal consumption. In the early phase of the response, coal consumption will respond negatively, and at the end of the 10-year period, the same negative response will be witnessed. The fact that oil and coal are jointly used to enhance energy use and energy needs in China is a good enough reason for the positive response of shocks from oil prices to coal consumption. On the contrary, the negative association between financial development and coal consumption is an equally enormous reason for the complete negative response of shocks from the financial sector to coal consumption.

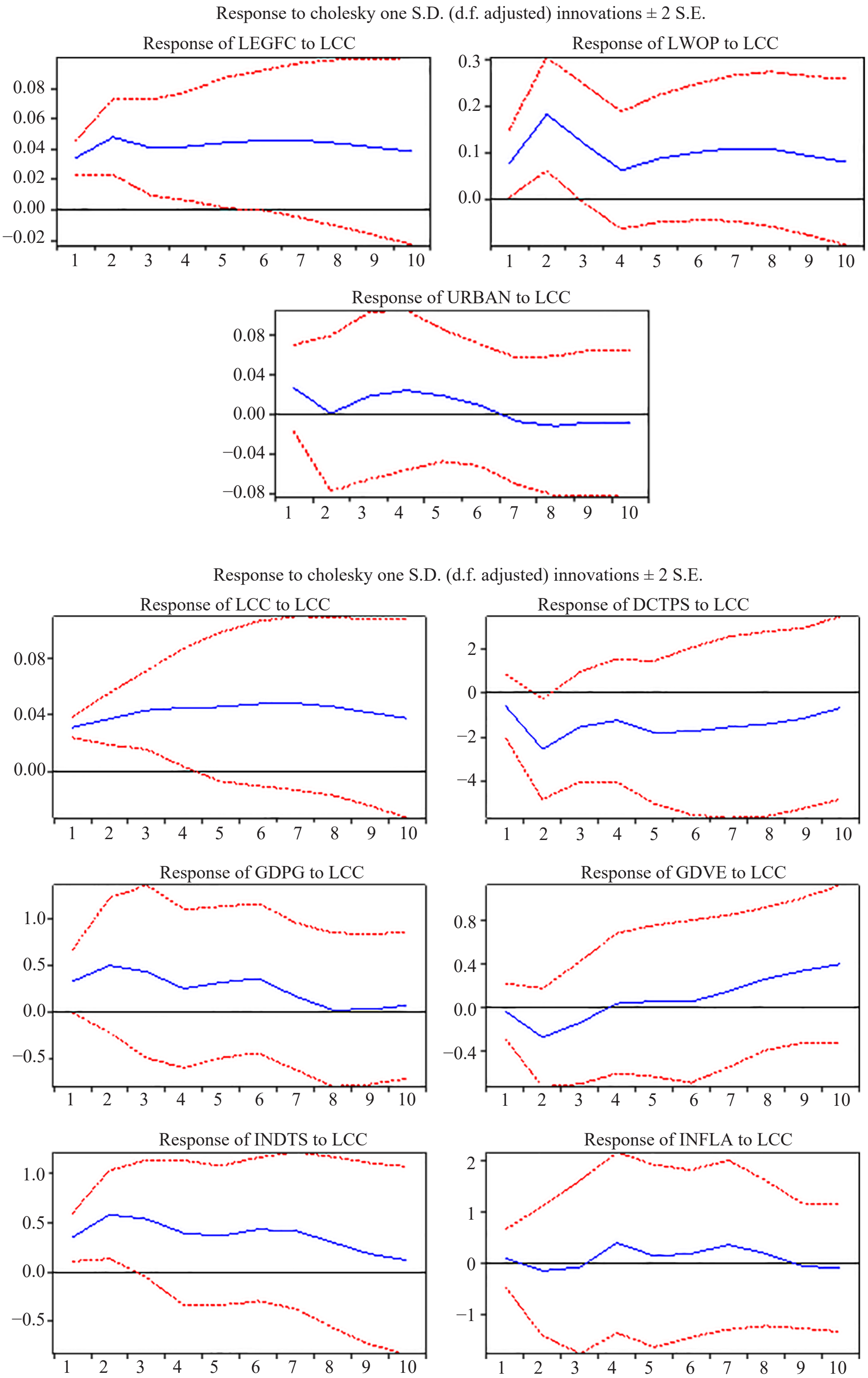

Figure 5. Impulse response

Source: Author's estimation

4.8 *Causality (Yoda Yamamoto)*

Table 10. Toda-Yamamoto

Direction	Chi square	Prob. value
LCC → URBAN	34.85215	0.0000***
DCTPS → LCC	13.20992	0.0014***
DCTPS → GOVE	4.971937	0.0832*
DCTPS → LEGFC	6.621967	0.0365**
DCTPS → URBAN	16.05139	0.0003***
GDPG → ALL	112.4750 (overall)	0.0000***
GOVE → INDST	8.179583	0.0167**
INDST → GOVE	5.875739	0.0530*
INDST → LEGFC	5.819702	0.0545*
INDST → URBAN	7.619804	0.0222**
INFL → INDST	8.425061	0.0148**
LEGFC → URBAN	9.260188	0.0098***
LWOP → (INDST, LEGFC, LCC, DCTPS, GDPG, INFL)	343.2503 (overall)	0.0000***
URBAN → DCTPS	5.613071	0.0604*
URBAN → INFL		0.0121**
URBAN → LWOP	5.368907	0.0683*

Source: Author's estimation

Note *** 1% significant, **5% significant, * 10% significant and overall represents the overall Prob value and chi-square

To explore the causal relationship between these highlighted variables, the Toda-Yamamoto conditional Granger causality test is used. The reason is that understanding the causality between them is necessary for developing strategies for coal consumption, trade policy, and environmental sustainability. Using a vector auto-regressive model with lag p that has a modified Wald test statistic, this method effectively investigates the direction of causality between these highlighted variables. In fact, this test outperforms the pairwise Granger causality technique, which implies all investigated variables must be integrated $I(0)$ or $I(1)$. Fortunately, the Toda-Yamamoto causality technique may be easily implemented and yield reliable findings if the investigated variables are integrated $I(0)$ or $I(1)$. From the results in Table 10 series of unidirectional causality flows, most importantly, we confirm that gross domestic output causes all variables under study. Relating to coal and economic growth, this one-way flow of causality is in line with the results of Wolde-Rufael (2010), Li and Leung (2012), Salima (2012), Korkmaz and Güvenoğlu (2021). There is one way causality between industrial development and urbanization. With reference to the tradition of settlement and demographic structure, industrial development is likely to boost or cause the rate of urban population. To seal the causality flow, the outcome from the Yoda-Yamamoto the outcome confirms that there is a bidirectional flow of causality between oil prices and economic growth. This means the occurrence of fluctuations in oil prices is as result of the changes in the growth rate of the Chinese economy and vice versa. This is entirely consistent with the findings of Adeosun et al. (2022).

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4.9 *Discussions*

The current study aims to investigate the determinants of coal consumption in China, as well as to monitor the behaviour of the regressors in both the long and short term. Findings begin with.

Which examined the behaviour of the variables using descriptive statistics of a common sample in Table 2. The study also examined the stationarity of the variables by conducting the unit root test for both Augmented Dickey Fuller (ADF) and KPSS Unit Root test in Tables 3 and 4. The result obtained from the unit root test displayed a similar out for both methods with a mixture of $I(0)$ and $I(1)$. From the result obtained from the unit root, the researcher concluded that it will be in best option to use the Autoregressive Distribution Lag (ARDL). The researcher also examines if there is a long-run association among the variables in Table 5 by employing by ARDL bound test to cointegration. It was discovered that Results of bound testing fall outside the Lower Bound and Upper Bound which represents the existence of a long-run association among variables. A lag selection test was conducted in Table 6 to reflect an accurate lag section instead of estimated lag. The lag length was chosen based on criterion result most suited for our model (Liew, 2004).

Tables 7 and 8 display tables of ARDL short run and long run results. Overall, the study highlights small-scale interactions between economic variables and coal consumption, with negative effects of economic growth, inflation, urbanization, and oil prices, while government spending and technological progress positively influence coal consumption.

In the long run, research shows that government expenditure (GOVE), industrial growth (INDST), GDP growth (GDPG), and coal-fired electricity generation (LEGFC) are positively related to coal consumption use (LCC) in China this means that coal is used as a common commodity. The positive relation between income and coal consumption in the general economy is in line with the work of Bloch et al. (2015). These data reveal that economic and technological developments along with government investments in infrastructure increase coal consumption. In addition, the study celebrates its unique contribution to addressing the impact of coal-fired power generation, economic growth and oil prices on coal consumption. The result between URBAN and LCC is not in line with that of Balmer (2007). Relating to coal and economic growth, this one-way flow of causality is in line with the results of Wolde-Rufael (2010), Li and Leung (2012), Salima (2012), Korkmaz and Güvenoğlu (2021).

Table 9 shows the residual diagnostic for the ARDL model, and it is obvious that there is no serial correlation or heteroscedasticity. In addition to this Jarque-Bera test result, it demonstrates that residuals are regularly distributed. In addition, the Cusum test confirmed the model's stability. The impulse response function (IRF) describes the impact of surprise on coal intake (LCC) through the years in Figure 5. The evaluation examines the reaction of the LCC to one or 2 well-known deviation shocks in phrases of different determinants, and well-known shows that cost is a critical issue. The examine uses a Cholesky decomposition to evaluate responses over a 10-yr length, noting the mild decline in coal intake after any such shock Inflation, generation, finance, and finance growth response shows a range of trends, with mild advantageous modifications due to monetary growth shocks and superb and poor over the years The responsive analysis concludes that oil charges positively have an effect on coal intake due to collective use of in terms of electricity production, even as economic growth shows steady negative effects. Finally, Table 10 shows the Toda-Yamamoto causality using a vector auto-regression model with a modified Wald test statistic, this study evaluates the direction of causality between published variables This method is more practical than the pairwise Granger causality technique and is easier to apply the Toda-Yamamoto causality technique of $I(0)$ or he changes the combination of variables in $I(1)$ the results show that GDP accounts for all the variables under investigation, that due to previous research by Wolde-Rufael (2010), Li and Leung (2012), Salima (2012), Korkmaz and Güvenoğlu (2021). Moreover, technological development unilaterally increases urban settlement, suggesting that technological development increases urban density. There is also a bidirectional causal relationship between oil prices and economic growth, which is consistent with the findings of Adeosun et al. (2022).

5. Conclusion and recommendations

Investigating which factors mainly gear coal consumption in China, the study confirms that GDP, financial development, inflation, urban development, and industrial improvements are the main determinants of coal consumption in China. To estimate how these determinants greatly influence the consumption of coal, the authors changed the raw data of some variables into their log form. The outcome shows that all variables have unit root problems except inflation and the log of world oil prices. This means that apart from inflation and oil prices, all the other variables are stationary at different orders of integration. The series log of coal consumption was observed to be integrated at first order, but at the 10% level of significance, to ensure uniformity of integration orders, we employed the KPSS unit root to check if it was possible for the series log of coal consumption to be stationary at first order. The result from the KPSS confirms the mixture of $I(1)$ and $I(0)$ orders of integration, setting the basis for the use of the auto-distributed lag model as a method of estimation.

With the above set of stationary and causal relationships, the auto-regressive distributed lag model estimation reveals that the variables considered are statistically significant and confirms that they are indeed strong determinants of or influencers of coal consumption in China. There is a positive link between coal consumption and economic development. In a microeconomic sense, we relate our argument to that of the income effect. From the result, we observe that an increase in the rate of national income will increase coal consumption, so we term coal a normal good. In magnitude, the outcome claims that coal consumption will improve by 0.004% if income increases by a percent ceteris paribus. We understand that population growth plays a vital and positive role, but in view of our estimate, we observe that as the urban area continues to witness a significant amount of growth, coal consumption levels will fall. This means coal consumption will no longer enhance population growth, and people in urban areas will tend to use other modern forms of energy in their homes, such as hydroelectricity.

As a possible policy recommendation, if the attainment of economic growth or GDP growth is the main goal of the government, it is also necessary for the government to encourage new and modern ways of generating power as the use of coal will decrease. Future investors aspiring to enter the coal mining business should pay attention to the fact that the movement of GDP growth is very essential in the decision-making process in the coal market, and how the urban population grows is equally essential to coal mining and consumption.

Conflict of interest

The authors declare there is no conflict of interest at any point with reference to research findings.

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