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LINEAR AND NONLINEAR LINKAGES BETWEEN EXHAUST POLLUTANT EMISSIONS, CO2 AND STOCK RETURNS IN CHINA

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ABSTRACT
This paper examines the effect of stock returns on exhaust pollutant emissions and CO2 emissions, considering the long run and short run perspectives. In doing so, the nonlinear ARDL (NARDL) methods is utilized and the datasets are covering from 2002 Q1 to 2018 Q4. The empirical findings based on NARDL results suggest that negative stock return shock is significant determinant of environmental quality variables but the positive stock return is insignificant. This suggests that the effect of stock return on environmental quality is subject to positive and negative stock returns. The lower stock return is associated with lower exhaust pollutant emissions and CO2 emissions. The impact of stock return on exhaust pollutant emissions and CO2 emissions come from negative stock return shock, and the short run impact is smaller than the long run. The quantile regression results demonstrate that at low and high exhaust pollutant emissions levels, stock return is insignificant. Nevertheless, at the middle exhaust pollutant emissions level, stock return is statistically significant in increasing exhaust pollutant emissions. The same finding is also detected when the CO2 emissions variable is used in the quantile regression.
Keywords: Exhaust Pollutant Emissions, CO2, Stock Return, China, NARDL.

1. Introduction
Exhaust pollutant emissions includes sulfur dioxide emissions, soot emissions and industrial dust emissions. It is an important factor affecting green GDP. In the green GDP accounting results, pollutant emissions and treatment costs are included, so how to reduce the exhaust pollutant emissions, it is very important. There are many factors that affect the emissions of exhaust pollutants. The influencing factors of air pollution are divided into socio-economic factors and environmental governance factors (Chenyu.2016). But in the past research, there are few articles about the relationship between the stock market and exhaust pollutant emissions.
After a large sample of empirical research, many foreign scholars found that air pollution will reduce investors' stocks return (Zhanggongfu. 2013). Professors (Tamir Levy) and (Joseph Yagil) used the air quality index and the stock return data of four stock exchanges in the United States to study the relationship between air pollution and stock investment returns. They found that the air quality index near the exchange was negatively correlated with the return on stock investment, that is, the more polluted the air near the exchange, the lower the return on investors' stock investment.

In the past ten years, the scale of China's stock market has grown by 238.9%, ranking second in the world in terms of market size, with more than 200 million stock market investors. The market is beginning to recognize the impact of carbon emissions risk on company value and stock returns, but the research of relationship between stock return and exhaust pollutant emissions in China still have not found.

There are mixed results of stock market on exhaust pollutant emissions and the findings are still inconclusive. Firstly, several studies have found that stock market has positive impact on environment, while others claim that stock market deteriorates environment quality (Mankiw & Scarth 2008; Pardy & Mundial 1992; Lanoie et al., 1997). Secondly, the stock market-environment quality nexus has bidirectional relationship, which green economy could affect stock market development (Paramati et al., 2017). Therefore, the main issue here is the inconclusiveness results emerged from past studies, and thus, stock market-green GDP -that takes into account environment quality- has remained an open question to be addressed.

In addition, stock market development is assumed to have improvement of environmental quality by promoting the use of green technologies (Paramati et al., 2018). Hence, the more developed the stock market, the more friendly energy production and reduction in activities with environmental degradation. Although the role of stock market on CO2 emissions and energy consumption is elaborated, stock market relationship on green GDP as an indicator of GDP without sources depletion, such as CO2 emissions, is not well established and discussed.

2. Literature Review

There are some studies to analyze the existence of an environmental Kuznets curve (EKC) considering the midst of renewable energy consumption, population, pollutants and economies. Simionescu et al. (2022) validate the so-called Environmental Kuznets curve (EKC) and the revised (or renewable energy) Kuznets curve (RKC) in ten Central and Eastern European (CEE) countries in the period from 1990 until 2019. Conditioned by data availability, the impact of governance in these countries on greenhouse gas (GHG) emissions is assessed in the period 2002–2019. The results based on the panel autoregressive distributed lag (ARDL) models indicated the contribution of renewable energy consumption in reducing pollution and the role of labor productivity in enhancing GHG emissions in the long run. In addition, such factors as the rule of law, regulatory quality and control of corruption were the governance dimensions that contributed to the environmental quality in the long run.

The study of Liton et al (2022) analyze the existence of an environmental Kuznets curve (EKC) considering the midst of energy consumption, population and economic development. The main objective is to investigate the impact of energy consumption, population and economic development on CO2 emissions. This study has taken data from 1971 to 2020 to see the existence of an EKC in the country of Bangladesh. Besides population growth, energy consumption and economic development are also taken into consideration. An autoregressive distributed lag (ARDL) model was used to scrutinize cointegration based on selected variables and their respective I (0) and I (1) values. This study has confirmed the long-term existence of the EKC in the environment. The environmental Kuznets curve was also tested using economic performance coefficients on emissions. In the long run, EKC ex-plains why per capita carbon output decreases with population expansion but turns down after a certain threshold level is achieved because of this inverted U-shaped pattern.

For decades, increased energy consumption has been linked to worsening environmental conditions, according to this study. Aslam et al. (2021) explores the relationship of CO2 emissions, gross domestic product, globalization, industrialization, and trade openness for Malaysia by using annual data for 1971–2016. By applying the ARDL bound testing approach, the estimates infer that CO2 emissions have steadily risen with high economic growth and affirm the U-shaped environmental Kuznets curve (EKC). Globalization' index and trade openness surge Malaysian CO2 emissions. While industrialization has a statistical and significant negative impact on CO2 emissions.

On the other hand, some studies have focused on financial development on environment effect. For instance, Yang and Ni (2022) studied 51 BRI countries' panel data from 2005 to 2017. The findings show that: BRI countries' financial development has a negative effect on the efficiency of green development in terms of financial size, financial deepening, and financial efficiency over the sample period. They also confirm the heterogeneity of the effect of financial development on the efficiency of green development when the various characteristics are taken into account. In addition, a study of Lv et al. (2021) using data from 30 provincial administrative regions in China from 2003 to 2017 found that financial structure, financial scale, and financial efficiency all have different effects on green technology innovation. The current financial structure, dominated by the banking sector, contributes to the acceleration of green technology innovation. The paper of Huang et al. (2020) examines the relation between air pollution and individual investors' trading behavior and performance. Using unique data on stock trades by 87,504 individuals from 34 cities in China, it finds a negative relation between air pollution and trade performance. This result is obtained after controlling for investor-year fixed effects and date fixed effects, as well as local weather conditions. More strikingly, abnormal trade performance decreases monotonically with the levels indicating the severity of air pollution. Furthermore, they find evidence suggesting that air pollution makes investors more susceptible to the disposition effect and attention-driven buying behavior. Overall, the results highlight a hitherto-unexplored cost that ambient air pollution imposes on stock market investors.

3. Methodology

3.1 Model Specification

This study adopts the Aslam et al. (2021) model with some modifications to analyze the objective one that related to environmental Kuznets curve (EKC). The dependent variable is exhaust pollution emissions (EPEM), the main interest independent variable is stock return, and other control variables are GDP, GDP square (GDP2), institutions (INS), population (POP), trade openness (TRAD), and renewable energy consumption (RENEW). The energy consumption is not included in the model due to this variable is highly correlated with GDP. All variables are converted to natural logarithm except the stock return variable. Therefore, the following is the baseline model of objective 1:

$$\boldsymbol{EPEM_t = \alpha + \beta_1\ STOCKR_t + \beta_2\ \mathrm{GDP}_t + \beta_3 GDP2_t + \beta_4\ INS_t + \beta_5\ POP_t + \beta_6\ TRAD_t + \beta_7 RENEW_t + \varepsilon_t} \quad Eq(1)$$

Besides using the EPEM, this study also uses the CO2 emissions to represent the environmental quality variable as dependent variable (CO2), where the independent variables are still similar with Equation 1 above.

$$CO2_t = \alpha + \beta_1\ STOCKR_t + \beta_2\ \mathrm{GDP}_t + \beta_3 GDP2_t + \beta_4\ INS_t + \beta_5\ POP_t + \beta_6\ TRAD_t + \beta_7 RENEW_t + \varepsilon_t$$
Eq(2)

where EPEM represents the exhaust pollutant emissions and CO2 is CO2 emissions in China, STOCKR represents stock market returns, GDP and GDP square represent the output and output square to test the EKC, INS is institutions quality, POP is population, TRAD represents trade openness and RENEW represents the renewable energy consumption, ε_t is the error terms. All the variables are in natural logarithm transformation except stock return (STOCKR) variable.

The controls variables are added in the equation above are based on theoretical and empirical postulation. For instance, based on the EKC theory, environmental pollution has inverted U-shaped nonlinear relationship with GDP. Initially, industrialization and an enhanced quality of life lead to high energy demand and hence increase environment degradation (Hussien et al., 2016; Sun et al., 2020). Nevertheless, when the GDP has achieved a high level, the development will shift to services sector and the government has the environmental quality policies protection. Therefore, the GDP and GDP square term are included to capture the nonlinear inverted U-shaped relationship. Better institutions tend to improve environmental quality and the expected sign of □4 is expected to be negative. Rapid population has a tendency to increase pollution and the expected sign for □5 is positive. Similarly, the trade openness increases exhaust pollution emissions or CO2 due to globalization and the expected sign for □6 is positive. On the other hand, renewable energy decreases exhaust pollution emissions or CO2 emissions, so the □7 is expected to be positive sign.

3.2 Estimation Methods

3.2.1 Stationary Tests

Two very important tests for stationary are Augmented Dickey Fuller (ADF) test and Philip Perron (PP) test. The ADF test is used to check the stationary of the variables and used for order of integration of the variables. This test uses extra lagged of the time series data to get rid of the autocorrelation in the residuals, and the lag length is determined by Akaike Information Criterion (AIC) or with Schwartz Bayesian Criterion (ABC) (Ahmad, 2012).

The ADF unit root test is based on the below equation of first difference and without intercept and trend:

$$\Delta Y_t = \partial Y_{t-1} + \sum_{i=1}^{p} B_i \Delta Y + \varepsilon_t$$

The below equation is with intercept:

$$\Delta Y_t = \alpha + \partial Y_{t-1} + \sum_{i=1}^{p} B_i \Delta Y + \varepsilon_t$$

Where the following below equation with intercept and trend (T):

$$\Delta Y_t = \alpha + \partial Y_{t-1} + \gamma T \quad + \sum_{i=1}^{p} B_i \Delta Y_{t-i} + \varepsilon_t$$

The hypothesis test of unit root test is that; the null hypothesis indicates that the estimated variable has unit root, whereas the alternative is; the estimated variable has no unit root or stationery. Therefore, the decision making is conditional on the p-value of the test. If the p-value is greater than the 5% significance level, it indicates that we fail to reject the null hypothesis and the variable is non-stationary. However, if the p-value is smaller than the 5% significance level we reject the null hypothesis and we conclude of stationary of the estimated variable. Additionally, conclusion can be made via the comparison between t-statistics and ADF critical value, if the t-statistics is greater than ADF critical value, thus, the variable is stationary. On the other hand, if the t-statistics is smaller than the ADF critical value, then we failed to reject the null hypothesis and the variable is non-stationary.

The PP test is developed by Philips and Perron (1988) where the equation of this test can be shown as follows:

$$\Delta \boldsymbol{Y_{t-1}} = \boldsymbol{\alpha} + \boldsymbol{\partial Y_{t-1}} + \boldsymbol{\varepsilon_t}$$

This test improves the t-statistics of the coefficient ∂ in order to remove the serial correlation in the error term. The PP test makes a correction to the t statistic of the coefficient ∂ from the AR(1) regression to account for the serial correlation in ε_t using nonparametric methods. Once the variable is stationary, then it is said to be integrated of order equal to the number of differencing.

It worth noting, the PP and ADF tests are known to have low power against the alternative hypothesis that the series are stationary with a large autoregressive root (DeJong, et al, 1992). Also, the ADF and PP tests are known to have crucial size distortion (in the direction of over-rejecting the null) when the series has a large negative moving average root (Joshi, 2015).

Ng and Perron (2001) and work by Elliott et al. (1996), new tests to deal with both of the mentioned issues. Their tests, in contrast to many of the other “new” unit root tests that have been developed over the years, seem to be a preferred alternative to the traditional ADF and PP tests. The family of Ng-Perron test has the following feature. Firstly, the Ng-Perron tests is a modified lag selection (or truncation selection) criterion. It turns out that the standard lag selection procedures used in specifying the ADF regression (or for calculating the long run variance for the PP statistic) tends to under fit, i.e., choose too small a lag length, when there is a large negative moving average (MA) root. This would create additional size distortion in unit root tests. Secondly, the time series is demeaned or detrended by applying a GLS estimator. This step turns out to improve the power of the tests when there is a large AR root and reduces size distortions when there is a large negative MA root in the differenced series (Joshi, 2015).

3.2.2 Nonllinear Autoregressive Distributed Lag (NARDL) Models

This study applies the ARDL approach as proposed by Pesaran and Shin (1999) and extended by Pesaran et al. (2001). There are bunch of reasons for the adoption ARDL. Mainly, the conventional Johanssen cointegration method uses a system of the equation to estimate the long-run relationship, while ARDL employs a single reduced form equation. Therefore, ARDL approach is an estimators that help to avoid the problem associated with the estimation of short time-series data (Enisan & Olufisayo, 2009). In addition, ARDL estimator does not require variables to be stationary at same level. Hence, it is applied regardless of whether the underlying variables are I(0) or I(1). Moreover, the long and short-run parameters of the model are estimated simultaneously.

$$\Delta lnEPEM_t = \alpha + \beta_1 lnEPEM_{t-1} + \beta_2 lnSTOCKR_{t-1} + \beta_3 lnGDP_{t-1} + \beta_4 lnINS_{t-1} + \beta_5 lnPOPG_{t-1} + \beta_6 TRAD_{t-1} + \sum_{i=1}^{n} b_i \Delta lnEPEM_{t-1} + \sum_{i=1}^{n} c_i \Delta lnSTOCKR_{t-1} + \sum_{i=1}^{n} d_i \Delta lnHC_{t-1} + \sum_{i=1}^{n} e_i \Delta lnINS_{t-1} + \sum_{i=1}^{n} j_i \Delta lnPOPG_{t-1} + \sum_{i=1}^{n} h_i \Delta ln\, TRAD_{t-1} + \varepsilon_t \quad Eq(3)$$

The bounds testing procedure is the first stage of the ARDL cointegration method and is based on the F-test or Wald-statistics. Therefore, a joint significance test that indicates no cointegration (H0: $\beta_1 = \beta_2 = \beta_{3=}\beta_4 = \beta_5 = \beta_6 = 0$) based on the Eq (1) above.

3.2.3 Quantile Regression

This method is used for robustness check of the previous method, which is applied to double confirm the augmented results and to confirm the robustness of the results and make a conclusion. Quantile regressions were first introduced by Koenker & Bassett (1978) as a robust regression technique that allows for estimation when the assumption of normality of the error term might not be strictly satisfied (Lee & Law, 2017). The quantile regression can be written as follows:

$$lnGGDP_t = X'_t\beta_\theta + \mu_{0t} \ : \quad Q_\theta(A_t/X_t) = X'_t\beta_\theta \qquad Eq(4)$$

Where $lnGGDP_t$_tdenotes China's green GDP, Xi is the vector of the independent variables, , $\beta_\theta$is the vector of parameters to be estimated for a given value of the quantiles θ. Where, $Q_\theta(A_t/X_t)$ is the θth quantile of the conditional distribution of the green GDP given the vector of explanatory variables Xi. In addition, quantile parameters are estimated by solving a minimization problem where the corresponding residuals have to be weighted. Notably, the robust covariance matric are computed by following the studies of Chamberlain (1994), Powell (1984), and Angrist et al. (2006).

The quantile regression has been used in growth studies (Mello and Perrelli, 2003; Osborne, 2006). The study of Mello and Perrelli in (2003) used quantile regression technique to examine the role of income convergence and the effects of policy variables on the conditional distribution of GDP. The findings using cross-sectional data evidenced of significant changes in the slope coefficients of independent variables across the quantiles. The second study of Osborne (2006) also considers how the coefficients on a number of standard growth determinants differ across quantiles; his results found significant differences across quantiles in the coefficients on the explanatory variables (Foster, 2008).

3.3 Data Description

The sample country of this study is China and the sample period is covering from 2002 to 2018 of 17 years, where the quarterly datasets are used in the analysis with 124 total observations.

The green GDP is calculated based on the formula mentioned earlier. Notably, the major source of the data for cities is the "China City Statistic Year Book". The Year Book provides information on cities' air and water pollution, financial development, economic index, and investment statistics among other statistics that will be used for this study.

For the independent variables, the financial stability variable is proxied by the bank z score. It captures the probability of default of a country's banking system, calculated as a weighted average of the z-scores of a country's individual banks (the weights are based on the individual banks' total assets). Z-score compares a bank's buffers (capitalization and returns) with the volatility of those returns. Stock return variable is proxied by stock return index retrieved from

Hushen300 DataStream source, this variable has been used by several previous studies for instance the study of Guidolin et al. (2009). The level of democracy refers to the annual index of POLITY2 which is derived from subtracting autocracy score (with the maximum score of −10 for full scale autocracy) from democracy score (with the maximum score of +10 for full scale democracy).

Political Stability and Absence of Violence measures perceptions of the likelihood of political instability, its index scale from 0 to 100, with 0 corresponding to lowest rank, and 100 to highest rank. Where human capital's proxy is life expectancy at birth, total (years), the data were taken from World Bank. In addition, openness is defined as the sum of exports and imports divided by GDP, the data of trade openness is obtained from World Bank. Population refers to total number of inhabitants of a given area or a country, population concentration is where the chunk of population is settled in a given location. In this study population is proxied by population density per square kilometer. Investment refers to financial commitments into business with aim of making returns from it.

While, environmental investment is retrieved from ministry of ecology and environment the People's Republic of China and this variable is the sum of urban environmental infrastructure investment, industrial pollution source control investment and "three simultaneous" project environmental protection investment. The last variable is exhaust pollutant emissions and also retrieved from ministry of ecology and environment the People's Republic of China, the variable includes Sulfur dioxide

Table 1: Summary of data description, sources and measurements of variables

Variables	Measurement	Data source
Carbon dioxide damage	Cost of damage due to carbon dioxide emissions from fossil fuel use and the manufacture of cement.	World Bank
Stock return (STOCKR)	Hushen 300 Increase and decrease (%)	Hibor economy database
Institutional quality (INS)	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism.	The Worldwide Governance Indicators.
GDP per capita (GDPC)	GDP per capita (constant 2010 US$).	World Bank national accounts data, and OECD National Accounts data files.
Trade Openness (TRAD)	Trade (% of GDP), Export plus import divided by GDP.	World Development Indicators.
Population (POP)	Population density.	World Development Indicators.
Exhaust pollutant emissions (PE)	It includes Sulfur dioxide emissions, soot emissions and industrial dust emissions	ministry of ecology and environment the people's republic of China

4. Results and Discussion

4.1 Descriptive statistics

Table 2 below presents the data statistics of the variables used for the objective one. The mean value of green GDP is 27.871 having a standard deviation of 0.753; stock return has an average value of 0.356, while its standard deviation is 1.478. Population shows an average value of 0.535 with a standard deviation of 0.057. The mean of human capital and investment are 18.315 (stand. dev. 0.616) and 10.570 (stand. dev. 0.789), respectively. The mean value of trade openness is 10.863 having a standard deviation of 0.817. The exhaust pollution emissions index ranges between 3.229 and 10.142.

Table 2: Descriptive Statistics

Variable	Unit of Measurement	Obs	Mean	Std Dev	Min	Max
GDP[1]	Yuan	68	30.018	0.447	29.20	30.018
Stock Return	Percent	68	0.356	1.478	-3.26	6.71
Population	Percent	68	0.535	0.057	0.419	0.692
Renewable energy		68	3.729	1.114	2.634	6.947
Institutions		68	14.743	1.372	11.921	17.608
Trade openness	% of GDP	68	10.863	0.817	8.677	11.981
Exhaust Pollution Emissions	Million tons	68	7.468	1.790	3.229	10.142
CO2 emissions		68	1.449	0.363	0.698	1.883

The correlation matrix is presented in Table 3 shows the relationship among the variables of interest used in this study. Variables of interest in this study are shown to have a negative correlation with Exhaust Pollution Emissions, however, population is positively correlate with exhaust pollution emissions. The highest correlation is indicated between trade openness and investment with 0.98, and other correlations are considered at reasonable level.

Table 3: Correlation Matrix

Variable	EPEM	RENEW	GDPSQ	INS	GDP	POP	STOCKR	TRAD	CO2
EPEM	1								
RENEW	0.4316	1							
GDPSQ	-0.8873	-0.5991	1						
INS	-0.7005	-0.3952	0.8455	1					
GDP	-0.8503	-0.7094	0.9852	0.6529	1				
POP	-0.5097	-0.4920	0.7407	-0.7853	0.7531	1			
STOCKR	-0.18570	-0.2844	0.2560	0.2057	0.2766	0.0940	1		
TRAD	0.8272	0.2323	-0.7517	0.9881	-0.7185	-0.3678	-0.2038	1	
CO2	-0.6592	-0.8975	0.8507	0.6617	0.9208	0.7445	0.3081	-0.5147	1

Notes: EPME=Exhaust Pollution Emissions, RENEW=Renewable energy, GDPSQ = GDP square, INS= Institutions, GDP=Gross Domestic Product, POP=Population, STOCKR=Stock return, TRAD=Trade openness

4.2 Results of Unit Root Tests

To use the ARDL approach, the unit root test is conducted to establish whether the time series is stationary at I(0) or I(1). The test is necessary to determine whether the time series is

[1] The GDP is in log form.

stationary or nonstationary to prevent the risk of misleading regression. The unit root is investigated in this study utilizing the Augmented Dickey Fuller (ADF) method (1979) and the Phillips Perron (1988). Table 4.3 shows the results of the order of integration of each variable. The variables show a mixture of I(0) and I(1), that some variables are stationary at level and first difference while others are not. However, all of the variables are stationary at first difference based on the results provided in Table 4

Table 4: Results of Unit Root Tests

Variable	Augmented Dickey Fuller (ADF)	Phillips-Perron (PP)
Level		
	Constant without trend	Constant with trend
GDP	-2.282	-4.111***
Stock return	-9.150***	-9.109***
Population	-1.898	-48.160*** 1(0)
Institutions	0.220	-3.978***
Trade openness	-1.277	-3.733** I(0)
renewable energy Exhaust	0.5592	0.9780
Pollution Emissions	0.209	1.838
First Difference		
	Constant without trend	Constant with trend
LGDP	-1.846	--20.021 ***
Stock return	-8.843***	-50.268***
Population	-2.352	-2.114
Institutions	-3.509***	-29.229***
Trade openness	-2.481	-14.7353***
renewable energy	0.5556 ***	0.0001 ***
Exhaust Pollution Emissions	-4.2905***	-9.555***

Note: *** and ** denote significant at 1% and 5% levels, respectively. Between the brackets are lag level.

4.3 Nonlinear ARDL Model and Bounds test

4.3.1 Stock Return- Exhaust Pollution Emissions

The nonlinear ARDL approach is applied for this objective, because the possibility of stock return asymmetric effect on exhaust pollution emissions in China in the long and short run. The NARDL model allows positive and negative shocks of stock return have any effects on exhaust pollution emissions. Table 16 reports the NARDL result of UECM model and the result is used to compute the long run and short run estimations.

Table 16 NARDL Unrestricted Error-correction Model
Dependent Variable: EPEM
ARDL(2, 1, 4, 3, 2, 4, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LEPEM(-1)	1.2167	0.1263	9.6327	0.0000
LEPEM(-2)	-0.3705	0.1105	-3.3532	0.0019
LGDP	-5.1407	1.4489	-3.5477	0.0011
LGDP(-1)	4.2291	1.2380	3.4160	0.0016
LGDPSQ	0.0388	0.0582	0.6659	0.5098
LGDPSQ(-1)	-0.0764	0.0361	-2.1109	0.0420
LGDPSQ(-2)	0.0659	0.0361	1.8242	0.0767
LGDPSQ(-3)	-0.0023	0.0011	-2.0836	0.0446
LGDPSQ(-4)	-0.0032	0.0016	-2.0216	0.0509
LPOP	10.996	2.3876	4.6054	0.0001
LPOP(-1)	-3.3212	1.6359	-2.0301	0.0500
LPOP(-2)	3.2946	0.9923	3.3199	0.0021
LPOP(-3)	3.0566	0.9965	3.0672	0.0042
STOCKR_POS	-0.0008	0.0024	-0.3629	0.7188
STOCKR_POS(-1)	0.0041	0.0042	0.9761	0.3357
STOCKR_NEG	0.0075	0.0040	1.8966	0.0661
STOCKR_NEG(-1)	0.0058	0.0052	1.1333	0.2648
STOCKR_NEG(-2)	-0.0017	0.0035	-0.4820	0.6328
STOCKR_NEG(-3)	0.0004	0.0028	0.1449	0.8856
STOCKR_NEG(-4)	0.0055	0.0023	2.3702	0.0234
LINS	1.8274	0.4593	3.9784	0.0003
LTRADE	-0.1549	0.0997	-1.5531	0.1294
LRENEW	-2.0909	0.4554	-4.5912	0.0001
LRENEW(-1)	1.5019	0.4707	3.1906	0.0030
C	-247.1279	78.3459	-3.1543	0.0033

Notes: EPME=Exhaust Pollution Emissions, GDP=Gross Domestic Product, GDPSQ = GDP square, POP = population, STOCKR_POS = stock return positive, STOCKR_NEG = stock return negative, , INS=Institutions, TRAD=Trade openness, RENEW=Renewable energy

The bounds test of cointegration is reported in Table 17 The F-statistic is 3.766 which is greater than the upper critical value of 1 percent. Therefore, this finding reveals that exhaust pollution emissions, gross domestic product, stock return, renewable energy, population and institutions and renewable energy consumption are moving together in the long-run.

Table 17: Bounds Cointegration Test

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.766014	10%	1.85	2.85
k	8	5%	2.11	3.15
		1%	2.62	3.77
Actual Sample Size	65		Finite Sample:	n=65

Table 18 presents the long run estimation result of NARDL model, the negative stock return shock is statistically significant determinant of EPEM. Mean that lower the stock return, higher the EPEM. However, positive stock return shock is insignificant determinant of EPEM. The GDP and GDP square coefficients are negative and positive but only the GDP is significant. This finding also is in line with the ARDL result where there is no EKC exist based on the data analysis even using the NARDL method. Again, higher the population tends to increase exhaust pollution emissions. The renewable energy consumption is negative associated with exhaust pollution emissions, where higher the renewable energy, lower the pollution. However, the institutions and trade openness variables are insignificant determinants of exhaust pollution emissions.

Table 18: Long Run Estimation between Stock Return and Exhaust Pollution Emissions

Table 18: Long Run Estimation between Stock Return and Exhaust Pollution Emissions

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	-5.9244	1.6895	-3.5066	0.0013
LGDPSQ	0.1474	0.3545	0.4160	0.6799
LPOP	91.157	16.348	5.5758	0.0000
STOCKR_POS	0.0503	0.0395	1.2714	0.2119
STOCKR_NEG	0.1149	0.0388	2.9627	0.0055
LINS	1.1945	1.6963	0.7041	0.4860
LTRADE	-0.2172	0.3689	-0.5888	0.5597
LRENEW	-3.8280	0.6491	-5.8966	0.0000
C	-1606.094	284.3502	-5.6482	0.0000

Notes: EPME=Exhaust Pollution Emissions, RENEW=Renewable energy, INS=Institutions, GDP=Gross Domestic Product, POP=Population, STOCKR=Stock return, TRAD=Trade openness

Table 19 reports the short-run dynamic model between stock return and exhaust pollution emissions. The error-correction term (ECT) is negative and significant, justify the short-run bounds cointegration test where the variables are moving together in the long-run. The negative stock returns are significant and affects exhaust pollution emissions, GDP, institutions, population, renewable energy and trade openness are significant determinants of exhaust pollution emissions in the short run but the expected signs are not followed the theory due to the short run is a dynamic process.

Table 19: NARDL Error Correction Regression (Stock Return- Exhaust Pollution Emissions)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Δ (LEPEM(-1))	0.3705	0.0806	4.5969	0.0001
Δ (LGDP)	-5.1407	0.7537	-6.8199	0.0000
Δ (LGDPSQ)	0.0388	0.0311	1.2479	0.2204
Δ (LGDPSQ(-1))	-0.0602	0.0252	-2.3903	0.0223
Δ (LGDPSQ(-2))	0.0056	0.0012	4.3782	0.0001
Δ (LPOP)	10.996	1.4000	7.8543	0.0000
Δ (STOCKR_POS)	-0.0008	0.0016	-0.5304	0.5992
Δ (STOCKR_POS(-1))	-0.0045	0.0027	-1.6698	0.1039
Δ (STOCKR_NEG)	0.0075	0.0028	2.7132	0.0103
Δ (LINS)	1.8274	0.3436	5.3181	0.0000
Δ (LTRADE)	-0.1549	0.0706	-2.1927	0.0351
Δ (LRENEW)	-2.0909	0.2786	-7.5043	0.0000
ECT(-1)	-0.1538	0.0223	-6.8807	0.0000

Notes: EPME=Exhaust Pollution Emissions, RENEW=Renewable energy, INS=Institutions, GDP=
Gross Domestic Product, POP=Population, STOCKR=Stock return, TRAD=Trade openness

4.3.2 Stock Return- CO2 Emissions

The nonlinear ARDL approach is applied for stock return and CO2 emissions, because the CO2 emissions is the very important part effect on eexhaust pollution emissions in China, particularly in the long and short run. The NARDL model allows positive and negative shocks have any impacts on CO2 emissions. Table 20 reports the UECM result between the positive and negative impacts of stock return.

Table 20: NARDL Unrestricted Error-correction Model
Dependent Variable: LCO2
ARDL(2, 0, 0, 2, 0, 0, 1, 0, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LCO2(-1)	1.4442	0.1043	13.837	0.0000
LCO2(-2)	-0.6231	0.0971	-6.4155	0.0000
LGDP	0.0841	0.0333	2.5222	0.0149
LGDPSQ	0.0002	0.0001	1.2320	0.2237
LPOP	1.4661	0.0777	18.866	0.0000
LPOP(-1)	-2.2786	0.1971	-11.558	0.0000
LPOP(-2)	0.9759	0.1678	5.8130	0.0000
STOCKR_POS	0.0005	0.0004	1.1611	0.2511
STOCKR_NEG	0.0007	0.0004	1.7628	0.0840
LINS	0.0633	0.0771	0.8205	0.4158
LINS(-1)	-0.2001	0.0833	-2.4020	0.0201
LTRADE	0.0198	0.0096	2.0612	0.0445
LRENEW	-0.5826	0.0651	-8.9370	0.0000
LRENEW(-1)	0.8647	0.1188	7.2735	0.0000
LRENEW(-2)	-0.3543	0.0804	-4.4057	0.0001
C	-5.4947	1.9383	-2.8347	0.0066

Notes: EPME=Exhaust Pollution Emissions, RENEW=Renewable energy, INS=Institutions, GDP=Gross Domestic Product, POP=Population STOCKR=Stock return, TRAD=Trade openness

The bounds test of cointegration is reported in Table 21 The F-statistic is 3.9065 which is greater than the upper critical value of 1 percent. Therefore, this finding reveals that CO2 emissions, gross domestic product, stock return, population and institutions, trade openness and renewable energy consumption are moving together in the long-run.

Table 21: Bounds Cointegration Test

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.906547	10%	1.85	2.85
k	8	5%	2.11	3.15
		1%	2.62	3.77
Actual Sample Size	66			

Table 22 presents the long run estimation result of NARDL model, the negative stock return shock is statistically significant determinant of CO2 emissions. This finding suggests that lower the stock return, higher the CO2 emissions. However, positive stock return shock is insignificant. The GDP and GDP square coefficients are positive but only the GDP is significant. This finding is consistent with the ARDL result where there is no EKC exist using the CO2 emissions and NARDL analysis. Again, higher the population tends to increase CO2 emissions. The institutions variable is negative and significant determinant of CO2 emissions, this implies that better institutions reduce CO2 emissions. However, higher the trade openness increases CO2 emissions since the trade openness coefficient is positive. The renewable energy consumption is negative associated with CO2 emissions where higher the renewable energy reduces CO2 emissions in the long run.

Table 22: Long Run Estimation (Stock Return and CO2 Emissions)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP	0.4704	0.1054	4.4610	0.0000
LGDPSQ	0.0011	0.0009	1.2039	0.2343
LPOP	0.9140	0.3254	2.8086	0.0071
STOCKR_POS	0.0028	0.0027	1.0461	0.3005
STOCKR_NEG	0.0041	0.0020	1.9661	0.0548
LINS	-0.7646	0.2899	-2.6369	0.0111
LTRADE	0.1107	0.0415	2.6666	0.0103
LRENEW	-0.4041	0.0515	-7.8494	0.0000
C	-30.722	5.4948	-5.5911	0.0000

Notes: EPME=Exhaust Pollution Emissions, RENEW=renewable energy, INS=Institutions, GDP=Gross Domestic Product, POP=Population, STOCKR=Stock return, TRAD=Trade openness

Table 23 shows the short-run dynamic model between stock return and CO2 emissions. The error-correction term (ECT) is negative and significant, justify the short -run bounds cointegration test where the variables are moving together in the long-run. The negative stock returns affect CO2 emissions, GDP, GDP square, population and renewable energy are significant of CO2 emissions in the short run.

Table 23: NARDL Error Correction Regression
(Stock Return and CO2 Emissions)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Δ (LCO2(-1))	0.6071	0.0822	7.3791	0.0000
Δ (LGDP)	0.1373	0.0529	2.5931	0.0122
Δ (LGDPSQ)	0.0002	9.81E-05	2.5802	0.0126
Δ (LPOP)	1.4176	0.0884	16.036	0.0000
Δ (LPOP(-1))	-0.9467	0.1415	-6.6904	0.0000
Δ (STOCKR_POS)	0.0002	0.0003	0.5341	0.5955
Δ (STOCKR_NEG)	0.0010	0.0004	2.4243	0.0187
Δ (LINS)	0.0662	0.0674	0.9825	0.3302
Δ (LRENEW)	-0.5786	0.0521	-11.1039	0.0000
Δ (LRENEW(-1))	0.3425	0.0674	5.0778	0.0000
Δ (LTRADE)	0.0033	0.0167	0.1996	0.8425
ECT(-1)	-0.1823	0.0319	-5.7068	0.0000

Notes: EPME=Exhaust Pollution Emissions, RENEW=renewable energy, INS=Institutions, GDP=Gross Domestic Product, POP=Population, STOCKR=Stock return, TRAD=Trade openness

4.4 Robustness Test Using Quantile Regression

This study also performs further robustness checks using the quantile regression. The quantile regression can evaluate the low, middle and high levels of dependent variable which is the pollution variable. In this model the dependent variable is EPEM and based on the quantile regression, this study evaluates the median unlike in the OLS which focuses on the mean. The results of the analysis showed that both stock return and human capital are positive, but insignificantly determinants of EPEM. While investment, GDP, population and institutions are statistically significant and negatively related to EPEM.

Figure 5 depicts the coefficients plot of various independent variables and the patterns of the coefficients evolve from low quantile to high quantile affect the dependent variable. The stock return diagram indicates that the coefficients increase from 10th per cent quantile until 40th percent quantile, then decrease until 70th per cent quantile, and rebound back or increase again from 80th quantile to 90th quantile. The coefficients of other independent variables throughout the quantiles also presents in Figure 4.5. Each variable shows upward and downward patterns that indicate lower quantile level and higher quantile levels with respect to EPEM dependent variable.

From the quantile analysis, this study uses different dependent variable namely CO2 emissions to obtain the coefficients for each quantile, the empirical results are reported in Table 24 The interest variable namely stock return has positive and statistically significant determinant of CO2 emissions at 5 per cent level, where the quantiles are 30th, 40th, 50th. This means that when the CO2 emissions are at the middle level, the stock return has an influence on environmental quality. However, at the low and high pollution levels of CO2 emissions, the stock return is insignificant determinant of CO2 emissions. This finding suggests that stock return is related to the environmental quality especially the environmental quality is at the middle level.

The GDP variable is significant determinant of CO2 emissions throughout all quantiles at 1 per cent level. Regardless the environmental quality is high or low, the GDP is always significant, which suggest that economic development harms environment quality in China. Nevertheless, the GDP square term is insignificant, this reveals that there is no Kutnez curve exist in China based on the quantile regression analysis. The coefficient is insignificant throughout all quantiles. Population is positive and significant determinant of CO2 emissions. The finding demonstrates that whether the CO2 is low or high, the population is contributed to CO2 emissions.

The institutions variable is negative and significant at all quantiles except 20th and 90th per cent. This indicates that institutions play an important role in reducing CO2 emissions such as better rule of law, government effectiveness, accountability and transparency, bureaucratic quality. Therefore, having good institutions are vital to reduce pollution. The trade openness which is measure of globalization shows that the coefficients are positive and significant at conventional levels throughout all quantiles. This suggests that irrespective environmental quality is low or high, openness tends to increase pollution. The renewable energy variable, which is measured by renewable energy consumption (% of total final energy consumption) shows that all coefficients have negative sign. This finding suggests that regardless the CO2 emissions are at low or high level, renewable energy tends to reduce the CO2 emissions and substitute to the energy used.

Figure 6 depicts the coefficient values of all variables used in the estimation. The stock return which is the interest variable shows upward trend, then downward from 30th to 50th quantiles. The coefficients tend to increase from 80th to 90th quantiles, but at the high level of pollution, the stock return is insignificant determinant of CO2 emissions.

Table 24: Robustness Checks using EPEM as environmental quality measure for pollution
Dependent variable: Exhaust Pollution Emissions (EPEM)

VARIABLES	(1) q10	(2) q20	(3) q30	(4) q40	(5) q50	(6) q60	(7) q70	(8) q80	(9) q90
LGDP	8.357	5.188	3.281	4.345*	5.498***	5.151***	5.146***	5.087***	4.880*
	(6.884)	(5.083)	(3.801)	(2.303)	(1.463)	(0.653)	(1.533)	(1.791)	(2.778)
LGDPSQ	-0.00377	0.000156	0.000951	-0.000190	0.00192	0.00958	0.00813	0.00399	0.00650
	(0.161)	(0.248)	(0.205)	(0.233)	(0.263)	(0.791)	(1.108)	(1.444)	(0.941)
LPOP	18.04***	18.38***	17.11***	16.65***	17.03***	12.23*	10.83	13.26	13.58
	(4.054)	(4.075)	(4.107)	(3.538)	(4.241)	(6.647)	(9.071)	(10.24)	(11.31)
STOCKR	0.0430	0.0572	0.0710**	0.0716**	0.0844**	0.0358**	0.0393	0.0541	-0.0118
	(0.0739)	(0.0805)	(0.0321)	(0.0363)	(0.0379)	(0.0179)	(0.113)	(0.102)	(0.0732)
LINS	-11.59	-13.72	-11.56	-9.486	-6.843	-3.921	-3.862	9.270	20.68
	(18.58)	(19.20)	(16.68)	(15.96)	(10.22)	(10.96)	(10.47)	(14.17)	(18.38)
LTRADE	2.990***	2.523**	2.740**	3.014**	3.033***	3.427**	3.826**	2.721	2.128
	(0.981)	(1.008)	(1.053)	(1.286)	(1.111)	(1.337)	(1.625)	(2.032)	(1.932)
LRENEW	-2.642	-3.423	-3.568*	-3.580	-3.821**	-2.644	-1.563	-4.089	-8.428
	(2.104)	(2.095)	(2.114)	(2.428)	(1.894)	(3.028)	(4.416)	(6.548)	(7.585)
Constant	-193.1**	-189.0*	-164.8*	-158.4**	-157.7**	-103.5	-110.1	-107.1	-22.25
	(96.30)	(106.8)	(82.42)	(78.94)	(65.46)	(81.82)	(119.1)	(113.1)	(123.2)
Observations	68	68	68	68	68	68	68	68	68

Notes: ***, ** and * denote significant at 1%, 5% and 10% levels, respectively. EPME=Exhaust Pollution Emissions, GDP=Gross Domestic Product, GDPSQ=Gross Domestic Product square, POP=Population, STOCKR=Stock return, INS=Institutions, TRAD=Trade openness, RENEW=renewable energy, , , ,

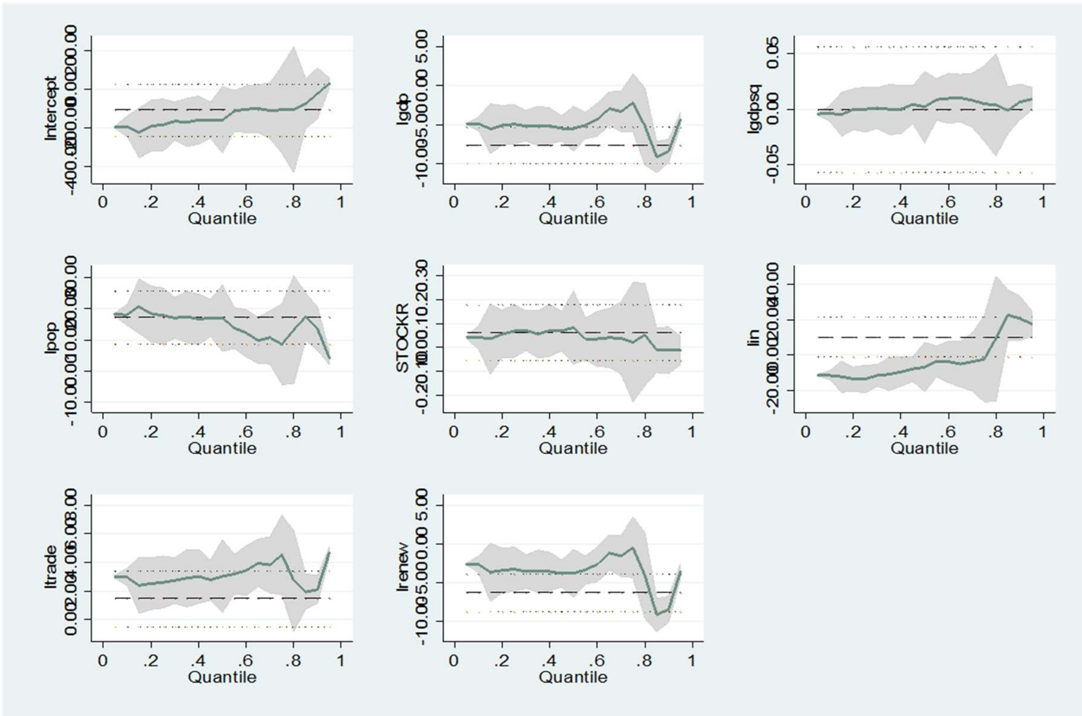

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Figure 5: The Coefficients of Various Quantiles of the Variables

Table 25: Robustness Checks using CO2 as environmental quality measure for pollution

Dependent variable: CO2 Emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	q10	q20	q30	q40	q50	q60	q70	q80	q90
LGDP	0.344***	0.373***	0.341***	0.359***	0.381***	0.402***	0.396***	0.411***	0.362***
	(0.0774)	(0.0855)	(0.0917)	(0.0819)	(0.0766)	(0.0524)	(0.0421)	(0.0344)	(0.0327)
LGDPSQ	-0.000272	-0.000135	0.000162	9.39e-05	0.000100	0.000211	0.000260	0.000220	0.000483
	(0.0292)	(0.0271)	(0.0271)	(0.0234)	(0.0222)	(0.0111)	(0.00808)	(0.00693)	(0.0112)
LPOP	1.325***	1.082***	1.190***	1.118***	1.036***	0.917***	0.951***	0.900***	0.998***
	(0.168)	(0.154)	(0.162)	(0.160)	(0.150)	(0.122)	(0.0805)	(0.0717)	(0.0752)
STOCKR	0.00276	0.00182	0.00305**	0.00365**	0.00234**	0.00174	0.00164	0.000564	0.00289
	(0.00162)	(0.00190)	(0.00149)	(0.00140)	(0.000933)	(0.000905)	(0.00108)	(0.00115)	(0.00153)
LINS	-0.612***	-0.343	-0.366**	-0.321**	-0.338***	-0.271**	-0.254**	-0.201**	-0.0740
	(0.204)	(0.229)	(0.183)	(0.126)	(0.119)	(0.114)	(0.101)	(0.0906)	(0.0743)
LTRADE	0.116**	0.174***	0.137**	0.161***	0.188***	0.195***	0.188***	0.205***	0.163***
	(0.0470)	(0.0534)	(0.0621)	(0.0546)	(0.0489)	(0.0366)	(0.0314)	(0.0273)	(0.0273)
LRENEW	-0.508***	-0.471***	-0.505***	-0.487***	-0.468***	-0.451***	-0.456***	-0.442***	-0.489***

	(0.0404)	(0.0449)	(0.0383)	(0.0362)	(0.0341)	(0.0380)	(0.0369)	(0.0374)	(0.0354)
Constant	-35.04***	-31.57***	-32.57***	-31.85***	-30.97***	-29.37***	-29.83***	-29.39***	-29.80***
	(2.416)	(1.855)	(2.050)	(1.849)	(1.659)	(1.490)	(0.982)	(0.936)	(0.983)
Observations	68	68	68	68	68	68	68	68	68

Notes: ***, ** and * denote significant at 1%, 5% and 10% levels, respectively. CO2=CO2 emissions, GDP=Gross Domestic Product, GDPSQ=Gross Domestic Product square, POP=Population, STOCKR=Stock return, INS=Institutions, TRAD=Trade openness, RENEW=renewable energy, , , ,

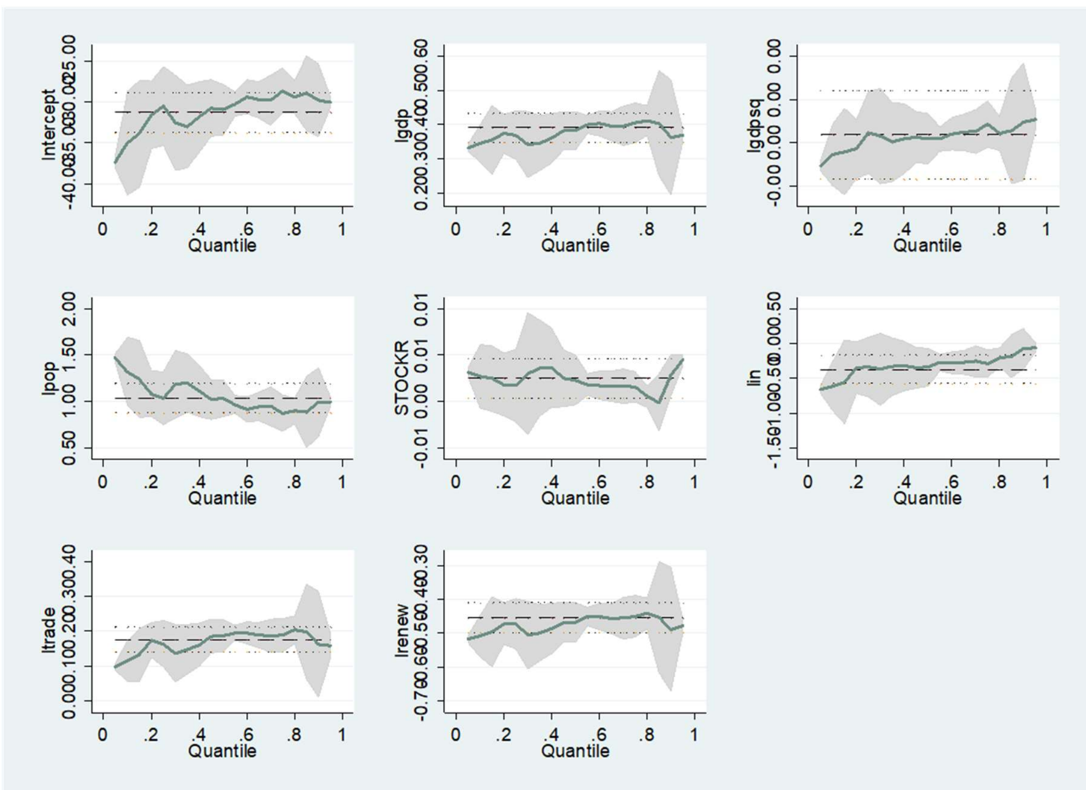

Figure 6: The coefficient plots of all CO2 emissions determinants

5. Conclusion

This study aims to investigate the link between stock return and environmental quality. The ARDL results show that the stock return is insignificant correlated with exhaust pollutant emissions in long run, but in NARDL model it shows that negative stock return is significant correlated with exhaust pollutant emissions in short run and long run. Other variables such as population and institutions are positive relationship with exhaust pollutant emissions, on the other hand, renewable energy is negative relationship with exhaust pollutant emissions, when decrease in renewable energy of 1% causes an increase in exhaust pollutant emissions of 1.26% in long run. This study includes the stock return-CO2 emissions link too. The ARDL results revealed that stock return shock is statistically significant determinant of CO2 emissions. The

NARDL model show that the effect is relative to negative stock return, positive stock return has no significant effect. It means most of the impact of stock return on CO2 emissions comes from negative stock return, and the short-term impact is much smaller than the long-term impact. It justified the short -run bounds cointegration test where the variables are moving together in the long-run. The GDP, institutions, population, renewable energy and trade openness are significant of CO2 emissions.

The quantile analysis is done for robustness check. The findings are, exhaust pollutant emissions increased by 6.73% in the 10th quantile, 6.71% in the 20th quantile, 6.41% in the 30th quantile, 9.81% in the 40th quantile, and then continued to decrease. The 80th and 90th quantiles of exhaust pollutant emissions are only reduced by 1.75% and 1.81%, respectively, by stock return. In addition, trade and human capital increases exhaust pollutant emissions from 10th to 90th quantile.

The robustness check of stock return on CO2 emissions indicated that stock return has a significant impact on CO2 only in the middle of quantiles that between 30% and 50%, however, it turns to insignificant when the quantile is very high or very low. The GDP variable is significant determinant of CO2 emissions throughout all quantiles at 1 per cent level.

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