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Towards sustainability: The effect of industries on CO_2 emissions

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A B S T R A C T

During the last decades, environmental crises through energy consumption and economic growth were noticed as a growing concern among researchers. The industrial sector is the main part of economic growth in each country using conservative energy and emitting carbon dioxide that causes global warming. The Paris agreement and Kyoto protocol were two agreements to prevent governments from emitting CO_2 freely. Purpose of this research was to investigate the cement industry, steel industry, and automobile industry products' effects on CO_2 emissions in Iran and to rank them according to their measured effects on CO_2 emissions. The methodology used in this study was to estimate equations with CO_2 emissions as a dependent variable and cement, steel, and automobile industries' products with ordinary least squares (OLS) and generalized moment method (GMM) approaches. Stationary, Johansen cointegration, Durbin-Watson, Breusch-Godfrey, Chow breakpoint, and normal residual tests were checked. In-sample forecasting was implemented to check the precision of the estimation and an updated ranking was reported as a final result to consider which industry has affected CO_2 emissions more than the others per unit of production cost. In conclusion, the cement industry, steel industry, and automobile industry had the most positive effects on CO_2 emissions, respectively. This result is suitable to prioritize the industries for enhancing green technology and optimizing industrial production for a more sustainable economy.

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1. Introduction

During the last decades, negative effects of rapid economic growth on the environment were noticed in research especially environmental hazards which is a crucial issue now. The main question was whether economic growth has environmental major problems due to emitting pollution like CO_2 emissions. To respond to the mentioned question, it is necessary to find out whether there are significant relationships between economic growth factors as independent variables and environmental hazard as the dependent variable. Some countries like Bangladesh had some policy implication problems due to their prime target which was to develop economic growth at the cost of environmental pollution to some degree (Kashem and Rahman, 2019). In recent years, experts have attempted to integrate sustainability into a variety of areas and businesses, including supply chains (Lotfi, Kargar, *et al.*, 2022; Lotfi, Rajabzadeh, *et al.*, 2022), construction (Rajabi, Radzi, *et al.*, 2022; Rajabi, Rezaeiashtiani *et al.*, 2022) and transportation (Beigi *et al.*, 2022; Rajabi *et al.*, 2023; Rajabi, Beigi, *et al.*, 2022). Energy consumption had a key role in economic growth. It caused many problems and hazards for the environment without paying attention to a sustainable economy (Yazdi & Mastorakis, 2014). Also, there is a growing interest in renewable energy as a procedure toward less polluting economic development and reaching international environmental protocols like the Kyoto protocol. Furthermore, renewable energy is a way to solve the rising costs of fossil fuels and energy security concerns. In Morocco, there was an increasing rate of energy consumption which was predicted to continue increasing for about 7 to 8.5 percent in the next ten years (Khanniba *et al.*, 2020). Ghasemi and Rajabi noted that enhancement of renewable energies and productivity is known as a solution for less greenhouse gases emissions and using updated data analytics can be helpful toward sustainable development (Ghasemi and Rajabi, 2023). Over the past two centuries, in addition to natural factors, human activities have raised greenhouse gases (GHGs), especially CO_2 emission which is believed to be the main cause of

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global warming. It was found that industrial production and the combustion of fossil energy were the main reasons for CO_2 emissions. 66 percent of global energy is used and 70 percent of CO_2 is produced in urban areas, but the cities have a noticeable share of the economic development of a country. Because of that, policymakers are putting much effort into mitigating the impact of global warming. Two solutions were to optimize industrial structures and to develop low-carbon technology for less CO_2 emissions (Wang *et al.*, 2015). After the 2008 financial crisis, green energy, low carbon economy, green growth, green economy, and enhancing productivity for more sustainable development have been noticed well. Using green technologies and renewable energies, especially in the industrial sector, is a road map toward a green economy that is required to gain more social and environmental benefits without economic growth reduction. The mentioned concept's advantages are sustainable economy, resource security, and providing more green jobs. Iran produced more than 552 million tons of carbon dioxide in 2015 and is among the top ten CO_2 emitters in the world. Furthermore, high subsidies on energy have caused more pollution released in this country (Solaymani, 2020). Overall, this is the first study to investigate the relationship between different industries' products and CO_2 emissions in Iran based on its importance for developing a green economy in this country.

2. Literature review

In this section, previous studies are reviewed. Yazdi and Dariani studied the relationship among CO_2 emissions, urbanization, economic growth, energy consumption, and trade openness in Asian countries with data from 1980 to 2014. Using pooled mean group (PMG) method and Granger causality tests, a bidirectional relationship was found for urbanization, economic growth, and CO_2 emissions. Higher urbanization could lead to more economic growth that came down to using more energy and more CO_2 emissions (Khoshnevis Yazdi & Dariani, 2019). Adusah-Poku also implemented research on the relationship between CO_2 emissions, urbanization, and population by studying sub–Saharan Africa. This research used the panel data from 1990 to 2010 and PMG for dynamic heterogeneous panels. It was found that growing urbanization and population could lower CO_2 emissions significantly in the short and long run. Moreover, it was concluded that CO_2 emissions grew faster due to energy use in more populated countries like Nigeria and Ethiopia than in less populated countries like Cape Verde and Equatorial Guinea (Poku, 2016). Katircioglu studied the environmental Kuznets curve (EKC) and the oil price effect on that in Turkey. In that study, it was found that oil prices in Turkey had a significant negative effect on CO_2 emissions which means directly that an increase in oil price could lead to less CO_2 emissions (KATIRCIOGLU, 2017). Hassoun et al. worked on the relationship between renewable energy, GDP, and carbon emissions in Algeria. Vector error correction model (VECM) and Granger causality were used to estimate the coefficients. It was found that in the short run, there was a positive bidirectional relationship between GDP and carbon emissions, but there was a negative unidirectional effect from renewable energy consumption on CO_2 emissions (Sari Hassoun *et al.*, 2019). İnal et Al. investigated the relationship among renewable energy, CO_2 emissions, and economic growth by studying African oil-producing countries. The data used in that research was for Angola, Algeria, Equatorial, Guinea, Egypt, Gabon, Congo Republic, Libya, Nigeria, and Sudan from 1990 to 2014. Second, generation panel data analysis was used to discover the relationship. The main goal was to find out the effect of CO_2 emissions and renewable energy on economic growth. As the results were shown in the article, renewable energy did not have a significant effect on economic growth while CO_2 emissions had a strong positive effect in Algeria, Equatorial Guinea, and Egypt. It was suggested to find an optimum criterion for the mix of renewable and traditional energy toward more sustainable economic growth (İnal *et al.*, 2022). Kasperowicz studied 18 European countries with data from 1995 to 2012 to find out the relationship between CO_2 emissions and economic growth. Error correction model estimation, panel unit root test, panel cointegration test, and estimated generalized least squares (EGLS) estimator were used in that research. It was concluded that in the short run, CO_2 emissions had a positive effect on economic growth, but in the long run, it had a negative effect. The results could be interpreted as improving technology for less pollution could not have a negative effect on economic growth in the long term (Kasperowicz, 2015). Bieth worked on the effect of GDP and human development index on CO_2 emissions. The research was done with the data of 6 countries in the association of southeast Asian nations (ASEAN) and Japan. Using panel data regression, it was found that GDP had an insignificant positive effect on CO_2 emissions, but human development index had an insignificant negative effect on that. It was suggested to work on the effects of other factors on CO_2 emissions to find more solutions for CO_2 reduction (Bieth, 2021). Pratama and Panjawa implemented their research to find the influence of gross domestic product (GDP), financial development, foreign direct investment, and energy on CO_2 emissions in Indonesia. The data used in that study was from 1990 to 2020. It was revealed that financial development and foreign direct investment had no significant effect on CO_2 emissions in short or long-run estimations, but GDP had an insignificant positive effect on CO_2 emissions in the short run and a significant positive effect on long-run estimations. It was suggested to focus on policy making for less use of energy in the industrial sector or production of renewable energy (Pratama & Panjawa, 2022). The following two studies are mentioned due to their methodologies which are close to this study's procedure. Ghanbari et Al. investigated the effect of U.S. dollar, gold and oil prices' effect on Tehran stock exchange market. The data used in that research was from April 2015 to March 2021. EViews software was used in that study to estimate linear equations for that purpose. Estimated linear equation was checked by several tests for validation and an in-sample forecasting was implemented to check the estimation's precision for forecasting. As a result it was found that gold and oil prices have a great effect on the stock market (Ghanbari *et al.*, 2022). Fooeik et al. investigated the effect of global oil, gold and palladium prices on Nasdaq index as an essential factor affecting investors' decisions. The data used in that study was from 2016 to 2021. In that study, EViews software was used to estimate equations to find the effects of each factor on the Nasdaq index. The results showed that gold and oil prices had a significant effect on the index while palladium price had less significant effect on that (Fooeik *et al.*, 2022).

As the studies are reviewed, in the first two articles it was found that more population and economic growth caused more CO_2 emissions. In the next study, a short-run positive unidirectional relationship was found between GDP and CO_2 emissions. In the next two studies, it was concluded that raising the oil price could decrease CO_2 emissions and mixing traditional and renewable energies could decrease pollution without GDP reduction. Improving technology for less pollution, studying other factors affecting CO_2 emissions, and focusing on the industrial sector for reducing pollution were suggested in the next three articles, respectively. As it was suggested, this is the first study focusing on the industrial sector to measure the effect of different main industrial products on CO_2 emissions. The methodology of this research is close to the methodologies of the last two reviewed articles.

3. Methodology

The purpose of the methodology was to estimate the long-term effect of three industries' production on carbon dioxide emissions and Iran is the case study of this research. For this purpose, cement industry, steel industry, and automobile industry were chosen to be investigated and to be ranked based on their coefficients. Statistical features, correlation, and covariance between the variables have been reported. Stationary tests were implemented for each data series and Johansen cointegration test was implemented as well. Next, an initial estimation was made. In the estimation, CO_2 emission was the dependent variable, and cement, steel, and automobile industries' products were the independent variables. Autoregressive (AR) and moving average (MA) terms could be added to the estimation as well. After initial estimation, probabilities of independent and ARMA terms were investigated to be significant. Durbin Watson, Breusch-Godfrey, normal residual, and Chow breakpoint tests were implemented for the estimation, respectively. Then, the generalized moment method (GMM) was estimated to compare the results with the initial estimation results. Moreover, in-sample forecasting was implemented for ten years and error terms were reported. In the final step, the industries were ranked according to their updated coefficients in GMM and initial estimations which were changed due to changes in their units to make the comparison accurate. The units of the coefficients changed from CO_2 emissions (thousand tons) per unit of production (thousand tons or vehicles) to CO_2 emissions (thousand tons) per unit of production cost (million Rials) to make all units of coefficients unique. Higher ranked industry in the ranking was known as a more effective industry on CO_2 emissions. The methodology procedure is shown in Fig. 1.

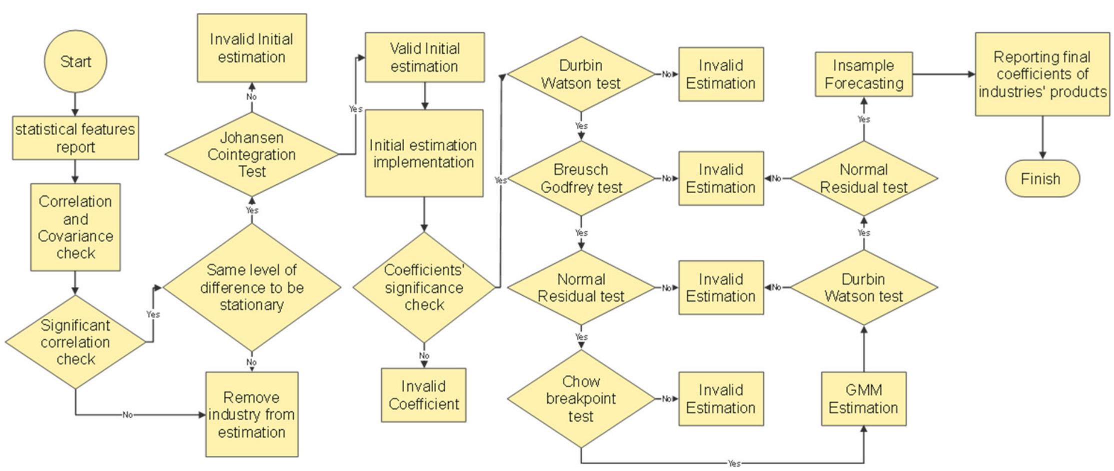

Fig. 1. Flowchart of methodology

The data on cement, steel, and automobile industries' production were collected from the central bank of Iran (CBI) (Central Bank of Iran, 2022). Also, the data on CO_2 emission was collected from the world data bank (WDI) (World Development Indicator, 2022). In this study, EViews_10 software was used, and the data was yearly from 1990 to 2019.

3.1 Statistical features, correlation and covariance

In this section, statistical features of each variable (CO_2 emissions, Cement industry production, Steel industry production, and Automobile production) were reported, and then covariance and correlation between the variables were calculated. Covariance illustrates the direction of a linear relationship between two variables, but correlation illustrates the direction and strength of the linear relationship. Correlation is a number between -1 and 1. If the number is closer to the negative or positive boundary, it shows a stronger negative or positive relationship, respectively.

3.2 Stationary test

In this section, the stationary of each data series was checked. Stationary means that there is no significant trend in the data series. This test is required because the data series without stationary can cause false regression which exists due to the data's trend. To solve this problem, the level of difference in the data can be increased. This means that if the data does not pass stationary tests, the difference between every two data in a sequence is calculated to form a new series and stationary tests are implemented on the new series. If the series does not pass the tests again, the level of difference is increased by one again and this process continues until finding the least level of difference in which stationary tests are passed. Being stationary is also known as the non-existence of a unit root. If a data series has unit roots in a specific level of difference, it means that the data is not stationary at that level of difference. In this study, the Philips-Perron (PP) test and Kwiatkowski-Philips-Schmidt-Shin (KPSS) test were used. PP test reports a P-value that confirms or rejects the null hypothesis. The hypothesis is that the data series has a unit root (is not stationary). If P-value is less than 10, 5, or 1 percent, this hypothesis can be rejected with an error of 10, 5, and 1 percent. KPSS reports LM-statistics which must be compared with asymptotic critical values of LM-statistics in 10, 5, and 1 percent. If this term is less than the asymptotic critical value of 5 percent level, it can be concluded that the null hypothesis is not rejected. The null hypothesis for the KPSS test is that the data series is stationary. For estimating a dependent variable with independent variables, the required level of difference between the dependent and independent variables for being stationary must be the same.

3.3 Johansen system cointegration test

In this section, Johansen cointegration test was implemented for CO_2 emissions, cement industry products, steel industry products, and automobile industry products. There is an assumption before the test that indicates whether the cointegration equation includes a trend or not. In this study, it was assumed that there is an intercept and no trend in the equation. There are two approaches for this test: Trace and Max Eigenvalue. Two null hypotheses are essential in these approaches. The first one is the null hypothesis of the non-existence of cointegration between the variables and the second one is the null hypothesis of the existence of cointegration at most 3. The second null hypothesis confirms that the cointegration existence between CO_2 emissions and all three industries' products is not rejectable. If the P-value of the first null hypothesis is less than 5 percent and the P-value of the second null hypothesis is more than 5 percent, it can be concluded that there is cointegration between CO_2 and the industries' products.

3.4 Initial estimation

In this section, an initial estimation was implemented with the ordinary least squares approach. After estimation, the P-values of each independent term's coefficient are reported to check whether the coefficient is significant or not. If P-value is less than 10, 5, or 1 percent, the coefficient is significant with 10, 5, or 1 percent, respectively. Moreover, ARMA terms can be added to independent variables to be estimated and to enhance the R-square statistic. The formulation of AR and MA models are shown in equations 1 and 2, respectively.

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_P y_{t-P} + \varepsilon_t \tag{1}$$

where y_t is the series value in time t, μ is intercept, ϕ_p is coefficient of y_{t-p} in time $t-p$, y_{t-p} is the series value in time $t-p$, ε_t is the error of estimation in time t and p is lag.

$$y_t = \mu + \theta_1 u_{t-1} + \theta_2 u_{t-2} + \cdots + \theta_q u_{t-q} + \varepsilon_t \tag{2}$$

where y_t is the series value in time t, μ is intercept, θ_q is coefficient of y_{t-q} in time $t-q$, u_{t-q} is the average of a number of previous data and the number is q. ε_t is the error of estimation in time t and q is the lag. In this study, the form of the initial estimation is shown in Eq. (3).

$$CO_{2_t} = \beta_0 + \beta_1 CIP_t + \beta_2 SIP_t + \beta_3 AIP_t + \theta_1 u_{t-1} + \varepsilon_t \tag{3}$$

where CO_{2_t} is carbon dioxide emissions (thousand tons), β_0 is intercept, β_1 is coefficient of CIP_t, CIP_t in cement industry product (thousand tons) in time t, β_2 is coefficient of SIP_t, SIP_t is steel industry product (thousand tons) in time t, β_3 is coefficient of AIP_t, AIP_t is automobile industry product (vehicles) in time t, θ_1 is the coefficient of u_{t-1}, u_{t-1} is the previous data in the time series (in time $(t-1)$) and ε_t is an error of estimation in time t.

3.5 Durbin-Watson, Breusch-Godfrey, Normal residual, Chow breakpoint tests

In this section, a number of required tests were implemented to make the estimation validated. First, the Durbin-Watson statistic was checked. The statistic measures the autocorrelation of residuals (ε_t) of the estimation. The boundaries of the

Durbin-Watson statistics are 0 and 4. If it is 2, that means no autocorrelation exists in the residuals. For an acceptable estimation, this statistic must be between 1.5 and 2.5.

Breusch Godfrey test is another test, used in this study to check the autocorrelation of the residuals. The Durbin-Watson test only checks the autocorrelation of residuals in the first order, but the Breusch-Godfrey test can check the autocorrelation in higher orders. If F-value is more than the F-statistic and the P-value is more than 5 percent, the null hypothesis is not rejected. The hypothesis is that the residuals of the estimation are not autocorrelated.

A normal residual test was implemented to check whether the residual distribution is normal or not. The P-value of the test must be more than 5 percent to make the normality of residuals acceptable.

The Chow breakpoint test was used in this study for stability checks. If the F-statistic of the data is less than the reported F-statistic of the test and the significance level is less than 5 percent, the null hypothesis is not rejected. The hypothesis is the stability of the data.

3.6 GMM estimation

GMM estimation is the same as initial estimation, but the approaches are different to report final coefficients. The ordinary least squares (OLS) approach which was used in the initial estimation is an analytical solution while GMM estimation's approach is to use a numerical solution and examines the results in an appropriate number of iterations. For more accuracy in this study, the GMM approach was used to compare its results with the initial estimation. The equation form of the GMM estimation is the same as equation 3. After estimating, Durbin-Watson and normal residual tests were checked.

3.7 In-sample forecasting

In this section, in-sample forecasting was used to check the estimations' precision. This was checked with the mean absolute percent error to be less than 5 percent.

3.8 Industries ranking in effect on CO_2 emissions and sustainability

In the last section, the investigated industries were ranked according to their coefficients in initial and GMM estimations. For an accurate ranking, it was required to measure each product with its production cost. That means calculating each coefficient per unit of production cost for each industry product. Then, it is correct to compare the calculated coefficients. Higher-ranked industries were interpreted as more critical ones in CO_2 emissions and sustainability. For this reason, the average production costs of the three industries were calculated with the data for the last 5-year available period which was from 2013 to 2017. The data was collected from the statistical center of Iran (Statistical Centre of Iran, 2022). Next, the calculated coefficients were updated to the new unit which was CO_2 emissions (thousand tons) per unit production cost of the industry product (million Rials).

4. Results

This section presents the results of the study in subsections in compliance with the methodology.

4.1 Statistical features, correlation and covariance results

Statistical features of CO_2, cement industry products, steel industry products, and automobile industry products data series were calculated and are shown in Table 1.

Table 1
Statistical features of CO_2 emissions, cement industry, steel industry, and automobile industry products

	CO_2	CEMENT	STEEL	AUTOMOBILE
Mean	431354.3	38100.21	10475.33	621351.2
Median	434225.0	32416.35	9297.000	709900.0
Maximum	637430.0	71000.00	26440.80	1429000.
Minimum	198470.0	15055.00	1583.600	19700.00
Std. Dev.	147242.5	19683.76	6371.788	472223.5
Skewness	-0.071852	0.326972	0.807882	0.139344
Kurtosis	1.501285	1.568516	2.913689	1.691729
Jarque-Bera	2.833498	3.095983	3.272682	2.236550
Probability	0.242501	0.212675	0.194691	0.326843
Sum	12940630	1143006.	314259.9	18640535
Sum Sq. Dev.	6.29E+11	1.12E+10	1.18E+09	6.47E+12
Observations	30	30	30	30

As it is shown in Table 1, all probabilities are more than 5 percent which proves that the normality of all four series is acceptable. Next, the covariance and correlation of each two series are reported in Tables 2 and 3.

Table 2
Covariance between each two variables

	CO_2	CEMENT	STEEL	AUTOMOBILE
CO_2	2.10E+10	2.64E+09	8.42E+08	5.99E+10
CEMENT	2.64E+09	3.75E+08	1.05E+08	7.42E+09
STEEL	8.42E+08	1.05E+08	39246355	2.14E+09
AUTOMOBILE	5.99E+10	7.42E+09	2.14E+09	2.16E+11

Table 3
Correlation between each two variables

	CO2	CEMENT	STEEL	AUTOMOBILE
CO2	1.000000	0.942307	0.928660	0.890767
CEMENT	0.942307	1.000000	0.863876	0.825307
STEEL	0.928660	0.863876	1.000000	0.735534
AUTOMOBILE	0.890767	0.825307	0.735534	1.000000

As it is shown in Table 3, the cement industry, steel industry, and automobile industry products have the most correlation with CO_2 emissions, respectively.

4.2 Stationary test results

PP test results and KPSS test results for the unit root test (stationary test) are reported in Table 4.

Table 4
Stationary tests of the data series

Data series	Level of difference	PP P-value	result	KPSS LM-stat.	KPSS LM-stat 5%	result
CO_2	1	0.0028	stationary	0.208	0.463	stationary
CEMENT	1	0.1174	Non-stationary	0.129	0.463	stationary
STEEL	1	0.0401	stationary	0.674	0.463	Non-stationary
AUTOMOBILE	1	0.0001	stationary	0.137	0.463	stationary

As it is shown in Table 4, at least one of the PP tests or KPSS tests accepts the data series of CO_2 emissions, cement industry products, steel industry products, and automobile industry products are stationary in the first level of difference. Based on this, the stationary of these data series was accepted in this study. As a result, cointegration existence between the data series is possible.

4.3 Johansen system cointegration test results

Johansen cointegration test was implemented on all data series to check the existence of valid long-term cointegration. The results of this test are reported in Tables 5 (Trace) and 6 (Max Eigenvalue).

Table 5
Johansen cointegration test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None *	0.771910	97.17422	54.07904	0.0000
At most 1 *	0.698298	57.26781	35.19275	0.0001
At most 2 *	0.491021	24.91329	20.26184	0.0106
At most 3	0.219145	6.678883	9.164546	0.1444

*P-value makes null hypothesis rejectable

Table 6
Johansen cointegration test (Max Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.
None *	0.771910	39.90641	28.58808	0.0012
At most 1 *	0.698298	32.35453	22.29962	0.0014
At most 2 *	0.491021	18.23441	15.89210	0.0211
At most 3	0.219145	6.678883	9.164546	0.1444

*P-value makes null hypothesis rejectable

As it is shown in Tables 5 and 6, the null hypothesis of the non-existence of cointegration between the data series is rejected and the null hypothesis of the existence of cointegration between all data series is not rejected according to both approaches. As a result, the assumption of cointegration existence between all data series is accurate.

4.4 Initial estimation results

In this section, an initial equation was estimated for CO_2 emissions as the dependent variable and cement industry products, steel industry products, and automobile industry products as independent variables. A moving average term in first order (q=1) was also added to estimate the dependent variable more precisely and to increase the R-square statistic. The estimation results are displayed in Table 7.

Table 7
Initial estimation results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CEMENT (CIP)	β_1=2.837657	0.999737	2.838404	0.0091
STEEL (SIP)	β_2=8.950281	1.580261	5.663798	0.0000
AUTOMOBILE (AIP)	β_3=0.083394	0.028789	2.896765	0.0079
C (β_0)	176520.1	17019.98	10.37134	0.0000
MA (1)	θ_1=0.718969	0.165173	4.352827	0.0002
SIGMASQ	3.48E+08	99640838	3.487789	0.0019
R-squared	0.983418	Mean dependent var		431354.3
Adjusted R-squared	0.979963	S.D. dependent var		147242.5
S.E. of regression	20842.45	Akaike info criterion		22.92848
Sum squared resid	1.04E+10	Schwarz criterion		23.20872
Log likelihood	-337.9272	Hannan-Quinn criter.		23.01813
F-statistic	284.6655	Durbin-Watson stat		1.545623
Prob(F-statistic)	0.000000			

As it is shown in Table 7, the P-values of the intercept (β_0) and cement, steel and automobile industry products' coefficients are significant due to their value of less than 5 percent. The moving average term of the first order (MA (1)) has a significant P-value due to the same reason as well. The R-square statistic is more than 98 percent which shows a high precision in the interpretation of CO_2 emissions and the probability of the F-statistic is less than 5 percent which shows that the accuracy of the estimation is not rejected.

4.5 Durbin-Watson, Breusch-Godfrey, Normal Residual, Chow Breakpoint results

In this section, the required tests for initial estimation validation were implemented. Durbin-Watson's value for the initial estimation was 1.54 according to Table 7. Due to its value between 1.5 and 2.5, autocorrelation between the residuals of the estimation was rejected. Breusch-Godfrey test results are illustrated in Table 8.

Table 8
Breusch-Godfrey test results

F-statistic	1.846292	Prob. F (3,26)	0.1636
Obs*R-squared	5.268618	Prob. Chi-Square (3)	0.1532
Scaled explained SS	3.646314	Prob. Chi-Square (3)	0.3023

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 12/13/22 Time: 12:43
Sample: 1990 2019
Included observations: 30

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	96055683	2.06E+08	0.465853	0.6452
CEMENT	4098.743	11236.04	0.364785	0.7182
STEEL	-20750.50	28931.05	-0.717240	0.4796
AUTOMOBILE	503.2193	348.2156	1.445137	0.1604
R-squared	0.175621	Mean dependent var		3.48E+08
Adjusted R-squared	0.080500	S.D. dependent var		5.20E+08
S.E. of regression	4.98E+08	Akaike info criterion		43.01550
Sum squared resid	6.46E+18	Schwarz criterion		43.20233
Log-likelihood	-641.2326	Hannan-Quinn criteria		43.07527
F-statistic	1.846292	Durbin-Watson stat		2.183295
Prob(F-statistic)	0.163586			

As it is displayed in Table 8, F-value is greater than the F-statistic and the P-value is more than 5 percent. As the result, the null hypothesis which is the non-existence of autocorrelation between the residuals in orders higher than one is not rejected. The normal residual test result is shown in Fig. 2.

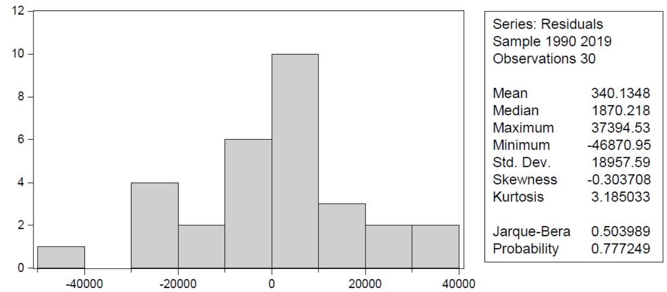

Fig. 2. Histogram of normal residual test

As it is shown in Fig. 2, the P-value of the normal residual test of the estimation is more than 5 percent and the distribution histogram almost shows a normal distribution. The Chow breakpoint test was implemented for the estimation to check the stability of the coefficients. This test divides the period of estimation into two sections. In this study, the midpoint of this period is chosen as the breakpoint which is the year 2005. The result of this test is shown in Table 9.

Table 9
Chow breakpoint test results

F-statistic	6.282781	Prob. F (6,18)	0.0011
Log likelihood ratio	34.61403	Prob. Chi-Square (6)	0.0000

As it is displayed in Table 9, due to F-value smaller than F-statistic and P-value less than 5 percent, it is concluded that the estimation null hypothesis which is the stability of the estimation is not rejected.

4.6 GMM estimation results

After the initial estimation and its required tests, GMM estimation was implemented in this study for more accuracy in results. The estimation outcome is shown in Table 10.

Table 10
GMM estimation results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CEMENT (CIP)	β_1=2.943221	0.347955	8.458634	0.0000
STEEL (SIP)	β_2=8.071398	1.206529	6.689765	0.0000
AUTOMOBILE (AIP)	β_3=0.082783	0.010097	8.198842	0.0000
C (β_0)	185533.3	7397.593	25.08023	0.0000
MA (1)	θ_1=0.815288	0.067759	12.03220	0.0000

R-squared	0.981659	Mean dependent var	447252.1
Adjusted R-squared	0.978470	S.D. dependent var	139093.2
S.E. of regression	20409.42	Sum squared resid	9.58E+09
Durbin-Watson stat	1.926192	J-statistic	5.126573
Instrument rank	12	Prob(J-statistic)	0.644520

As it is illustrated in Table 10, all P-values are less than 5 percent and as a result, all coefficients are significant. Moreover, the R-square statistic is more than 98 percent which shows a high precision in the interpretation of CO_2 emissions. Durbin-Watson test value is 1.92 which is between 1.5 and 2.5 and as a result, the residuals of the GMM estimation are not auto-correlated in the first order. The normal residual test result of the GMM test is reported in Fig. 3.

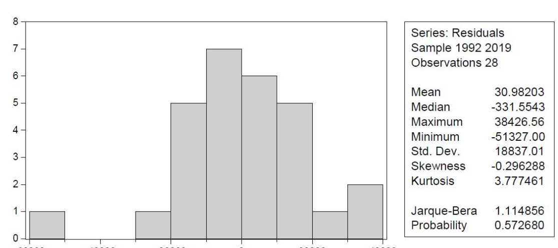

Fig. 3. Histogram of normal residual test

As it is shown in Fig. 3, the P-value of the test is more than 5 percent which shows that the distribution of the residuals is normal. It can also be seen that the distribution is almost normal.

4.7 In-sample forecasting results

In this section, in-sample forecasting was implemented to check its error. The results can reveal whether the estimations are meticulous enough for forecasting. In-sample forecasting results of the initial estimation and the GMM estimation are displayed in Fig. 4 and Fig. 5.

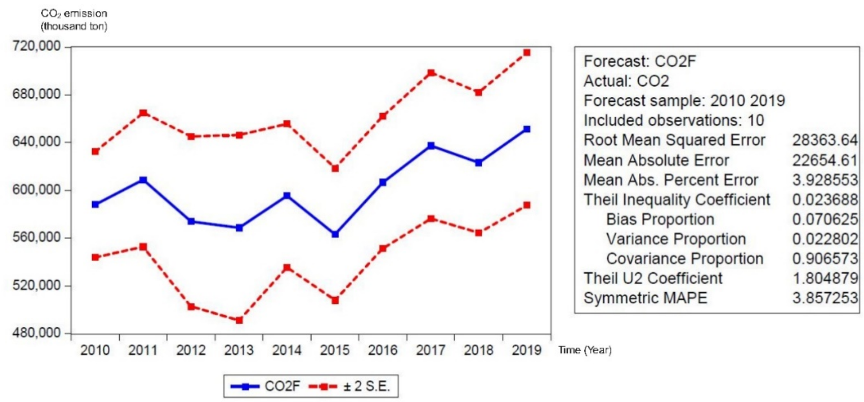

Fig. 4. In-sample forecasting results (Initial estimation)

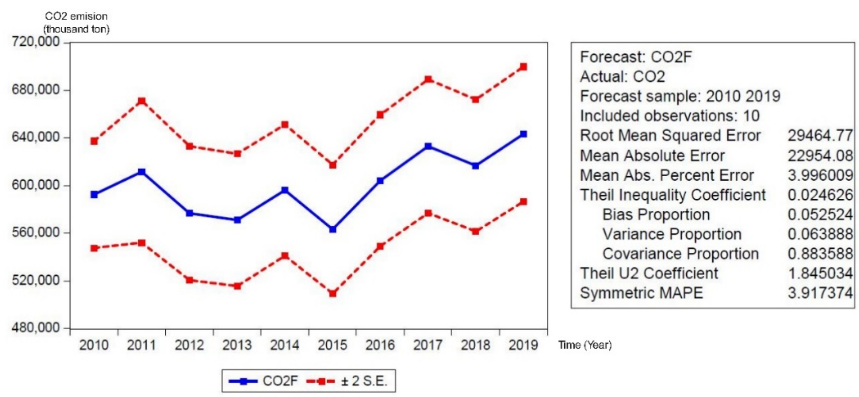

Fig. 5. In-sample forecasting results (GMM estimation)

As it is shown in Fig. 4 and Fig. 5, the root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE) of the initial estimation is better than GMM estimation. Moreover, the MAPE of both results is less than 5 percent which indicates a very good precision for forecasting.

4.8 Industries ranking in effect on CO_2 emissions and sustainability results

After the two estimations, the coefficients of each industry's products and their effect on CO_2 emissions were revealed. The coefficients of the industries are reported in Table 11.

Table 11
Industries' estimations' coefficients

Industry Product	Unit	Initial estimation coefficient	GMM estimation coefficient
CEMENT	Thousand tons	β_1=2.837657	β_1=2.943221
STEEL	Thousand tons	β_2=8.950281	β_2=8.071398
AUTOMOBILE	Vehicles	β_3=0.083394	β_3=0.082783

As it is displayed in Table 11, steel industry products increase CO_2 emissions by almost 8.5 thousand tons per each thousand tons of its production, cement industry products increase CO_2 emissions by almost 2.9 thousand tons per each thousand tons of production, and automobile industry products increase CO_2 emissions by almost 0.8 thousand tons per each vehicle production.

For comparing these industries, it is required to measure each product with its production cost as it was explained in the methodology to make the comparison accurate. The average production cost of cement, steel, and automobile industries' products based on the data from 2013 to 2017 was 1287 million Rials per thousand tons, 32968 million Rials per thousand tons, and 368 million Rials per vehicle. The updated coefficients with new units are reported in Table 12.

Table 12
Industries' CO_2 emissions ranking

Industry Product	Unit	Updated Initial estimation coefficient	Rank	Updated GMM estimation coefficient	Rank	Final Rank
CEMENT Production cost	Million Rials	0.002204861	1	0.002286885	1	1
STEEL production cost	Million Rials	0.000271483	2	0.000244825	2	2
AUTOMOBILE production cost	Million Rials	0.000226614	3	0.000224953	3	3

5. Conclusion

The purpose of this research was to consider major industries in Iran and investigate their CO_2 emissions. First, the stationary test and Johansen cointegration test were implemented to check whether the equation estimation was validated or not. Second, the initial equation was estimated with the OLS approach and then it was checked by the Durbin-Watson test, the Breusch-Godfrey test, the normal residual test, and the Chow breakpoint test. Third, GMM estimation was estimated for more accuracy in the coefficients' results, and it was checked by the Durbin-Watson test and normal residual test. Fourth, in-sample forecasting was done for both estimations to check their precision in forecasting. Finally, the industries were ranked according to their coefficients. As the results reported, cement industry, steel industry, and automobile industry had the most effect on CO_2 emissions, respectively. For policymakers, it is recommended to put the industries in the mentioned order to develop their green technology and green policies more effectively. Also, it is concluded that the OLS and GMM estimations were meticulous enough to use the industries' products for CO2 emissions forecasting. At the time of this study, the data was available from 1990 to 2019. In addition, two types of estimations were checked to find the industries' coefficients. For further study, it is recommended to use more available data if it is possible and use more types of estimations to check the accuracy of the coefficients.

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