The Impacts of Environmental Policies on Natural Gas Consumption in Iranian Industrial Sector

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ABSTRACT

This study aims to evaluate the effects of environmental policies, including price and non-price policies, on natural gas demand in Iranian industrial sector. To this end, considering the dynamic nature of our panel data, we adopted a generalized method of moments (GMM) model to estimate natural gas consumption for 22 Iranian industries from 2005 to 2015. The results state that the average annual natural gas consumption has been rising, reaching five times higher than the consumption of other fossil fuels. Among the industries, nonmetallic minerals industry with 8% of the total production of industry sector and more than 25% of natural gas consumption was regarded as the most natural gas consumer. The results of our GMM model show that non-price environmental policies are more effective than the price policies on natural gas consumption. Overall, in non-price policies, energy intensity seems more important than CO2 emission reduction. We therefore recommend that governmental energy policies should focus more on energy intensity improvement in Iranian industries through technological enhancement and fuel energy saving regulations.

1.Introduction

With the consumption of more than 225 trillion cubic meters, Iran was the world's fourth largest consumer of natural gas after the United States, Russia, and China in 2018. The share of natural gas in total fuel consumption in Iran increased from 20% in 2007 to 68% in 2018 (BP Statistics, 2019). This upward trend and an inappropriate energy consumption pattern has led to an increase in energy consumption, especially in natural gas. The largest share of natural gas consumption was domestically in the electric power sector (32%), residential and commercial sector (29%), and the industrial sector (27%) in 2016 (Iran Energy Balance, 2016).

Considering the environmental issues and the depletion of world oil reserves, the share of natural gas in the energy portfolio has been on the rise in recent years. Iran is one of the largest gas producing countries in the world, and the production capacity is higher than the demand for injection into oil reservoirs and domestic consumption. Natural gas can also be used as the raw material for the production of petrochemical and refining products in a liquid form. Iran's energy policy is based on promoting gas consumption instead of other liquid fossil fuels due to the abundant gas reserves.

There are several environmental policies, including price and non-price policies, such as improvements in technologies

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to save energy and promote natural gas consumption instead of fossil fuels to reduce greenhouse gas emissions in Iran. However, whether theses environmental policies have played an effective role in natural gas consumption in Iranian industrial sector or not is not clear. Thus, this research aims to identify the effects of environmental policies on natural gas demand in Iranian industrial sector and to provide a model for predicting the amount of this demand in the coming years. Considering the issue raised in this research, the following questions may arise:

- What are the impacts of the environmental policies on the demand for natural gas in the Iran industry section?
- What would be the influences of the non-price policies such as the improvement of technologies, the improvement in energy consumption efficiency, and the reduction of CO^2 emissions on the demand for natural gas in Iran industrial sectors?
- How does the change in pricing policies alter the tendency of Iranian industrial users from other fuels toward natural gas?

Investigating the impacts of environmental policies, including price and non-price policies, on natural gas demand in Iran industries through a model based on generalized method of moments (GMM) is the major contribution of the present paper.

The rest of the paper is structured as follows. In section two, we will introduce an overview of energy consumption and CO_2 emission in Iranian industrial sector. We will review the relevant domestic and international literature in section three. Then, in section four, we will discuss the methodology and design of research, including the data and the econometric model. Section five as the main part of the research is devoted to the estimation of the research model and the analysis of the empirical findings. Eventually, section six presents conclusions and policy implications derived from the research model.

2. An Overview to Energy Consumption and CO_2 Emissions in Iranian Industrial Sector

We provide a general overview of gas consumption in Iranian industrial sector, including the average annual natural gas and fossil fuel consumption and production, energy intensity, and CO_2 emissions from 2005 to 2015 in this section. Table 1 demonstrates that the development of other nonmetallic minerals industries with just 8% of production demands 25% of natural gas and 56% of other fossil fuels consumption and produces 53% of CO_2 emissions. Table 1 tabulates energy consumption and CO_2 emission in Iranian industrial sector.

The average annual total natural gas consumption in Iranian industrial sectors from 2005 to 2015 is equivalent to 151,616,403 barrels of oil, of which 37,963,536 barrels (about one fourth of total) are consumed by other nonmetallic mineral products industry as the largest consumer of natural gas in Iranian industries. The average annual total fossil fuel consumption in Iranian industrial sector from 2005 to 2015 is equivalent to 33,582,554 barrels of oil, of which 18,906,086 barrels (about 56%) is consumed by manufacturers of other nonmetallic mineral products as the largest consumer of fossil fuels in Iran industries. Comparing the natural gas and fossil fuel consumption reveals that Iranian industries consume natural gas about five times more than fossil fuels.

The average annual total production in Iranian industrial sector from 2005 to 2015 is 709,609 billion Rials (based on Rial value in 2011), while coal production industries and oil refineries with a value of about 196,059 billion Rials (based on Rial value in 2011) (about 28%) are the biggest producer of Iranian industries. The average annual total energy intensity in Iranian industrial sector from 2005 to 2015 is equivalent to 4.82 barrels of oil per billion Rials (based on Rial value in 2011), while the energy intensity of the production of other nonmetallic minerals, which is equivalent to about 1.06 barrels of oil per billion Rials (based on Rial value in 2011) (about 22%), is the highest figure in Iranian industries. The average annual total CO_2 emissions in Iranian industrial sector from 2005 to 2015 is 112,242,667.7 tones, of which 59,667,229.1 tones (about 53%) is the CO_2 emissions of other nonmetallic mineral products industry as the largest amount of CO_2 emissions in Iranian industries.

3. Literature Review

In this section, previous studies on industries demand for natural gas is reviewed. This section is divided into two subsections: the first subsection explains general studies on the demand for natural gas, and the next subsection reviews previous reports forecasted the demand for natural gas based on the environmental policies.

Interests in estimating natural gas have led to a remarkable number of researches in the last decade (Aydin, 2014). World energy demand has amplified abruptly as primary energy sources are required for sustainable development (Azadeh et al., 2015). Energy is connected to industrial production, agricultural output, access to healthy water, education, quality of life, cooking, and transportation (Xiong and Wang, 2014). Around one-fifth of the world prime energy is provided by natural gas which is the cleanest burning fossil fuel (BP, 2019; Xiong and Wang, 2014). Many studies have predicted natural gas production, consumption, as well as prices and income elasticity in several diverse areas at a regional level, world level, city level, national level, and individual customer level in industrial and residential sectors(Tonkovic et al., 2009). These studies used numerous data which could be classified into three main groups: meteorological data, historical data, and economic data. The first experimental study on the prediction of natural gas demand was conducted by Balestra and Nerlove (1966), while the first theoretical study was that of Hubbert (1949).

In 2004, Kaboudan and Liu derived a multi-regression equation system for short-term US demand for genetic planning (GP) and forecasted gas consumption in all four domestic, commercial, industrial, and electrical sectors. They indicated that the demand for each part is considered as a function of gas price, the price of the energy carrier, the economic conditions, and other control variables.

Aras (2004) conducted a study in Turkey and showed the significant motivation behind the demand for natural gas, with private gas consumption accounting for about 18% of the total gas consumption. Investigations into the anticipation of future

Table 1- Energy consumption and CO_2 emission in Iranian industrial sector

ISIC CODE	Industry	Natural Gas Consumption (%)	Fossil Fuel Consumption (%)	Production (%)	Energy Intensity (Amount)	CO_2 Emissions (%)
2732	Production of other nonmetallic minerals	25.04%	56.30%	8.17%	1.06	53.16%
2320	Coal production industries-oil refineries	16.20%	14.04%	27.63%	0.28	13.08%
1548	Food and beverage industries	5.50%	11.35%	8.82%	0.22	12.66%
2700	Basic metals production	23.82%	4.65%	13.90%	0.98	5.21%
2411	Chemical products industry	22.95%	3.57%	16.86%	0.33	4.17%
1721	Production of textiles	1.16%	2.30%	2.28%	0.21	2.78%
3410	Production of motor vehicles, trailers, and semi-trailers	1.07%	1.78%	8.40%	0.05	1.97%
2811	Manufacture of metal products except for machine tools	0.61%	1.20%	2.80%	0.08	1.37%
2899	Manufacture of machinery and equipment unclassified elsewhere	0.82%	1.06%	2.84%	0.10	1.24%
2100	Production of paper and paper products	0.97%	1.04%	0.65%	0.49	1.21%
2413	Production of rubber and plastic products	0.78%	1.00%	2.06%	0.14	1.08%
3110	Machinery and equipment for the generation and transmission of electricity	0.35%	0.47%	2.13%	0.06	0.57%
2022	Production of furniture and artifacts	0.14%	0.36%	0.42%	0.12	0.42%
2022	Production of wood, wood products, and cork	0.23%	0.27%	0.33%	0.22	0.35%
3599	Manufacture of other transport equipment	0.08%	0.21%	0.61%	0.06	0.26%
2926	Tanning and making leather and bags and luggage	0.04%	0.12%	0.18%	0.11	0.16%
2424	The production of medical, optical, and precision instruments and clocks	0.06%	0.12%	0.49%	0.05	0.14%
2221	Publish, print, and reproducing recorded media	0.06%	0.06%	0.31%	0.07	0.06%
3230	Production of radio, television, and communication devices	0.03%	0.04%	0.33%	0.05	0.05%
2422	Fabric manufacturing and coloring of fur skin	0.03%	0.03%	0.18%	0.06	0.04%
3000	Manufacturing of administrative and computing machinery	0.01%	0.02%	0.23%	0.02	0.02%
1600	Production of tobacco products from cigarettes	0.06%	0.00%	0.38%	0.04	0.00%

Source: Current work findings

gas interests have an incredible significance since natural gas is a source of foreign vitality. Aras proposed a method to obtain model fitting for gauging private month to month natural gas utilization. The technique depends on separating a year into two seasons as warming and non-warming periods and evaluating individual autoregressive time arrangement models for each period as opposed to achieving the regular examples in a solitary model.

Huntington (2007) examined the use of natural gas in the United States in order to develop an empirical model for evaluating future trends. This research derived a statistical model for the US consumption of natural gas based on data from 1958 to 2003, focusing on intermediate fuel switching facilities and changes in the industrial economy.

Keshavarz Haddad and Mirbagheri Jam (2007) studied the impacts of natural gas consumption, air temperature, natural gas prices, and consumer income on natural gas demand in Iran during 1995-2004. The coefficients estimated using the maximum likelihood method show that gas consumption per capita has a reverse relation with the price of electricity. Based on structural time series model (STSM) modeling, they found that temperature, the price of natural gas relative to electricity price, and income are the most important factors in predicting natural gas demand in Iran.

Seyyed Javadin et al. (2011) predicted the consumption of natural gas in the horizon of the fifth economic, social, and political development program of the country. Their results show that climatic conditions affect the consumption of natural gas in the domestic and public sectors, and the consumption behavior of the power plants and the domestic sectors complement each other in two different periods.

Abooniori and Ghafouri (2011) evaluated the factors influencing the supply of and the demand for natural gas in Iran using the auto regressive integrated moving average (ARIMA) model during 1976-2007 in a study up to the horizon 2025. They showed that the elasticity of short-term income and the price elasticity of natural gas demand are equal to 0.44 and 0.048 respectively, and long-term income and price elasticity were 8.8 and 1.68 respectively. Short-term and long-term natural gas export elasticity were predicted to be 0.13 and 0.25. Using estimated models in this work, natural gas supply and demand in the country are projected in the horizon 2025 in three optimistic, cynical, and pessimistic scenarios. According to this forecast, the growth of supply of and demand for natural gas in the first scenario are 4.5% and 3.5% respectively; these figures in the second scenario are 3.9% and 3.6% respectively, and they are 1.2% and 51.3% respectively in the third scenario.

Bianco et al. (2014) studied consumption drivers through a single demand model. They developed a model of the long-term forecast of nonresidential gas consumption in Italy based on historical data from 1990 to 2011. They also applied a sce-

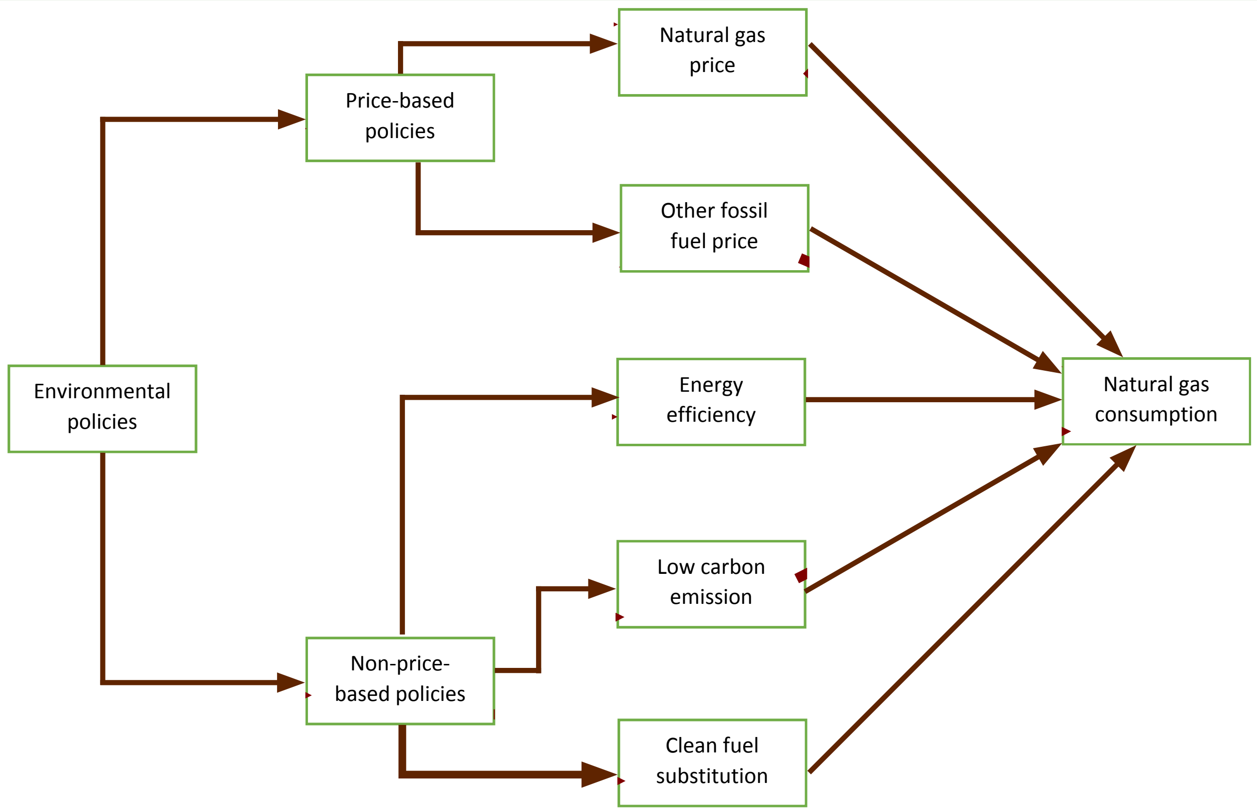

Figure 1: The conceptual model of the present study

nario analysis developed by analyzing twelve different cases.

Arshad Khan (2015) investigated short-term and long-term natural gas demand through econometric models based on the data during 1997-2011and showed that the gross domestic product had a greater impact on natural gas consumption in Pakistan compared to the development of natural gas price and elasticity price.

Zeng (2017) proposed a gray model called TPGM to simulate and forecast the supply of and demand for natural gas in China. They predicted the demand for natural gas in China during 2015-2020 and discovered that 67.61% of the consumption of natural gas will depend on foreign imports in 2020 due to a surge in demand for natural gas in China.

Gautam and Paudel (2018) studied the demand for natural gas in the residential, commercial, and industrial sectors of Northeastern United States using annual state-level panel data over the period 1997-2016. The estimated results showed that own price elasticity of demand for natural gas in residential, commercial, and industrial sectors is -0.14, -0.29, and -0.28 respectively in the long run. The cross-price elasticity of fuel oil for natural gas demand in residential, commercial, and industrial sectors are 0.19, 0.52, and 0.24 respectively. The natural gas demand is not affected by income in all the three sectors in the long run.

The second category of studies focused on natural gas demand and environmental policies.

Li et al. (2011) predicted demand for natural gas based on a dynamic model of the system for China in 2020 and 2030. Since 67% of China's energy supply was based on coal consumption, environmental considerations have led to a shift in energy from coal to natural gas. Thus, the forecasted consumption of 89.5 billion cubic meters of natural gas in 2010 will reach 198.2 billion cubic meters in 2020 and 340.3 billion cubic meters before 2030 in China.

Soldo (2012) examined the prediction model of residential gas consumption based on solar radiation. The results, based on linear models such as the automotive regression model and nonlinear models such as the neural network model, showed that the demand for residential natural gas affected solar energy supplies.

According to the work of Zeng and Li (2016), environmentally conscious manufacturing (ECM) has become an important strategy and proactive approach for the iron and steel sector of India to produce environmentally friendly and to reduce manufacturing costs. There are several environmentally conscious manufacturing indicators to evaluate ECM programs. Among those indicators, energy consumption and greenhouse gas (GHG) emission may be considered critical environmentally conscious manufacturing indicators (CECMI) for Indian iron and steel sector. They focused on forecasting energy consumption and GHG emission for a pig iron manufacturing organization of India. The selection of the correct ARIMA models of these indicators helps with accurate forecasting and achieving better environmental management practice.

According to the work of Xu and Lin (2016), energy saving and a decrease in carbon dioxide outflow in China are increasingly being considered worldwide. China has been on display in a period of rapid urbanization and industrialization, reflected in the rapid development of the use of vitality and carbon dioxide (CO_2) outflows. In addition, urbanization has an enormous impact on CO_2 emissions due to the mass urban foundation and the development of land. Financial development has a greater effect on emission reduction than industrialization due to the monstrous settled resource speculation and modern vitality improvement.

Mirzaei and Bekri (2017) argued that climate changes and a global temperature boost as the key dangers of human social order are essentially linked to the use of vitality and CO2 emissions. In this study, a dynamic framework model was developed to demonstrate the vitality utilization and CO2 emission patterns for Iran during 2000–2025.

Ozman et al. (2018) forecasted natural gas demand for residential consumers on the basis of multivariate adaptive regression splines (MARS) and conic multivariate adaptive regression splines (CMARS). The effect of monthly temperature variations between 2009 and 2012 was investigated based on the temperature degree (degree day). Moreover, the results were compared to neural network models and linear regression.

A review of the above researches related to natural gas consumption and environmental policies revealed that demand for natural gas is affected by price policies, including decreasing natural gas price and increasing other polluting fuels, and non-price policies, including energy efficiency, low carbon emission, and clean fuels substation. Therefore, the conceptual model of our study can be drawn as follows:

4. Methodology

This paper investigates the effect of environmental policies, including price and non-price policies, on natural gas consumption in Iranian industrial sectors during 2005-2015 for 22 Iranian industrial sectors. Price-based environmental policies include decreasing natural gas price and increasing the price of other fossil fuels consumed in Iranian industrial sectors. Although there are no clear non-price environmental policies for reducing pollutants, we used CO2 emission and energy intensity as proxies for these policies. Other factors such as sectoral productions used as a proxy for measuring economic growth over the period of the study.

As seen in the literatures related to economic and dynamic modeling, many economic relationships are dynamic in nature, and one of the advantages of longitudinal data is that the researcher can better understand the dynamics of adjustments. Dynamic relationships or models are represented by the presence of a lagged dependent variable among the independent variables (regressors), as follows:

yit=δyi,t-1+ βx'it+uit i=1,…,N; t=1,…,T (1)

where, δ is a scalar, and xit is 1×K; β = K×1. thus, uit follows a one-way error model:

$u_{it}=u_i+v_{it}$ (2)

where $u_i \sim IID(0,\sigma_\mu^2)$ and $v_{it} \sim IID(0,\sigma_v^2)$are independent of each other. The regression of the dynamic panel data described in Equation (1) is characterized by two sources of persistence over time. There is autocorrelation due to the presence of a lagged dependent variable among the independent variables and the individual effects characterizing the heterogeneity among the individuals.

Thus, in dynamic panel data models, when a dynamic relationship between variables should be estimated, common models used to estimate consistent and efficient coefficients are not applied. In other words, using estimate approaches based on ordinary least squares (OLS) (pooled OLS), fixed effects, random effects (generalized least squares (GLS) estimator) are not recommended in these models. Several ways in the literature are reported to estimate dynamic models; the first model is based on correcting the bias by using instrumental variables (Anderson and Hsiao, 1981) and the second one applies GMM estimation techniques.

4.1. Generalized Method of Moments (GMM) Model

Generalized method of moments (GMM) is preferred to a number of estimators developed by utilizing the sample moment counterparts of population moment conditions of the data generating model (Hansen, 2001). GMM estimators have become popular for the following main reasons:

- GMM estimator has great sample properties which can easily be characterized in a way which facilitates comparison. A number of these estimators can be studied a priori in a way which makes the comparison of asymptotic efficiency easy. The method is also appropriate to construct tests which explain both sampling and estimation errors (Hansen, 2007).
- In practical studies, researchers have recognized that GMM estimators can be constructed without specifying the generating process of all of data. This characteristic has been used to examine partially specified economic models in studying potentially mis-specified dynamic models designed to match target moments and in constructing stochastic discount factor models which link asset pricing to the sources of macroeconomic risk (Hansen, 2007).

4.2. Arellano and Bond (AB) Estimator Based on GMM

The dynamic panel data approach is usually considered the work of Arellano and Bond (AB) estimator. Arellano–Bond estimation starts by transforming all regressors, usually by differencing, and uses the generalized method of moments; it is also called difference GMM (Roodman, 2009).

It is based on the notion that the instrumental variables approach does not exploit all of the information available in the sample. By doing so in a generalized method of moments context, more efficient estimates of the dynamic panel data model may be constructed (Baum, 2013). Arellano and Bond argue that the Anderson–Hsiao estimator, while consistent, fails to take all of the potential orthogonal conditions into account.

To examine autocorrelation, the Arellano–Bond test is applied to the residuals in differences. Because $\Delta\varepsilon_{it}$ is mathematically related to $\Delta\varepsilon_{i,t-1}$ via the shared $\varepsilon_{i,t-1}$ term, a negative first-order serial correlation is expected in differences, and its evidence is uninformative. Thus, to check for the first-order serial correlation at levels, we look for the second-order correlation in differences based on the idea that this will detect the correlation between ε_(i,t-1) in Δε_it and $\varepsilon_{i,t-2}$ in $\Delta\varepsilon_{i,t-2}$. In general, we checked the serial correlation of order at levels by looking for the correlation of order n+1 in differences.

To test the identifying restrictions (the validity of instruments), we would use Sargan test proposed by Sargan in 1958. Sargan test assumes that model parameters are identified via a priori restrictions on the coefficients and tests the validity of over-identifying restrictions (Sargan, 1958). The test statistics can be calculated by residuals from the regression of instrumental variables by making a quadratic form based on the cross-product of the residuals and exogenous variables.

4.3. Econometric Model and Variables

Considering the structure of our data, i.e. several different Iranian industries for 11 years, dynamic panel data analysis seems an appropriate method. Panel data provide us with the majority of data, increasing the degrees of freedom and reducing the collinearity behind explanatory variables, thereby developing the efficiency of econometric estimates.

The success of dynamic panel data patterns in forecasting economic variables in this kind of data has led these models to be used broadly for predicting economic variables, formulating the behavior of variables, and eventually forecasting their future values. However, the question which remains in place is practically “which model, and on what basis, should be chosen from the various panel data?” The answer to this question is important, and in many studies, only one of the aforementioned patterns (without the steps described in the research methodology section), has been selected as a prediction model. The

Table 2-Summary of the variables, measurements, abbreviations, and the sources of data.

	Variable Name	Measurement	Abbreviation	Data Source
1	Natural Gas Consumption	Barrels of oil equivalent (BOE)	NGASC	Statistical Center of Iran
2	Energy Intensity	BOE/Billion Rial production in 2011	ENERIN	Iranian Energy Balance Sheet
3	CO2 emissions	Million tons per year	CO2EM	Reports of Ministry of Energy
4	Production	Billion Rials (based on Rial in 2011)	PRO	National Portal of Statistics
5	Natural Gas Price	Rial per cubic meter (based on Rial in 2011)	NGASP	Ministry of Energy of Iran
6	Average of Fossil Fuel Price	Rial per liter (based on Rial in 2011)	AVPFF	Calculation of Authors

present study seeks to develop a systematic approach to how to determine the principle of an appropriate dynamic panel data model for prediction in applied studies.

Considering conceptual models and theories, the function of demand for natural gas consumption in Iranian industrial sector will be as follows:

$$NGASC_{i,j}=f(PRO_{i,j}, ENERIN_{i,j}, CO2EM_{i,j}, AVPFF_{i,j}, NGASP_{i,j}) \quad (3)$$

(i=2005, 2006… 2015. j=1, 2… 22)

where, $NGASC_{i,j}$ is natural gas consumption in the ith year of the jth industrial sector; $PRO_{i,j}$ represents the industrial production as a measure of the output in the ith year of the jth industrial sector, and $ENERIN_{i,j,h}$ stands for energy intensity in the ith year of the jth industrial sector. $CO_2EM_{i,j,h}$ is CO_2 emissions in the ith year of the jth industrial sector. $AVPFF_{i,j}$ represents the average price of fossil fuels in the ith year of the jth industrial sector, and $NGASP_{i,j,h}$ stands for natural gas price in the ith year of the jth industrial sector.

Based on our data, because many of the data such as the total of fossil fuel consumption, CO2 emissions, and natural gas consumption are large, for more accurate calculation, we transferred the variables onto a logarithmic scale and calculated the elasticity of the variables. Hence, our final model is given by:

$$Ln(NGASC)=\alpha_1 Ln(PRO)+\alpha_2 Ln(NGASP)+ \alpha_3 Ln(AVPFF)+\alpha_4 Ln(CO2EM)+\alpha_5 Ln(ENERIN)+b_0 \quad (4)$$

We also defined average of fossil fuel price (AVPFF) based on the below formula:

$$AVPFF=\frac{P_{Gasoil}\times C_{Gasoil}+P_{kerosene}\times C_{Kerosene}+P_{FuelOil}\times C_{Fuel\ Oil}+P_{GasOline}\times C_{GasOline}+P_{Liquid\ Gas}\times C_{Liquid\ Gas}}{C_{Gas\ oil}+C_{Kerosene}+C_{Fuel\ Oil}+C_{GasOline}+C_{Liquid\ Gas}} \quad (5)$$

4.5. Diagnostic Tests of Dynamic Panel Data

Before model estimation, some tests, including Pesaran's cross-sectional dependence test (CD Test), unit root test, cointegration test, F-Limer test, and Hausman test must be performed to examine the incorporated variables.

In econometrics, panel data is generally assumed to have cross-sectional independence. This assumption cannot be similar to other assumptions, so the first step in the econometric analysis of panel data before any test is to test cross-sectional independence in error terms. To this end, this paper applies Pesaran's cross-sectional dependence test (2004). If there is cross-sectional dependency in the model, then using some of the stationary tests such as Levin, Lin, and Chu (LLC) test and Im, Pesaran, and Shin (IPS) test leads to unreal results, and these tests cannot be used to check the stationary of the model variables. In such a case, it is suggested that cross-sectionally augmented Dickey–Fuller (CADF) and cross-sectionally Im, Pesaran, and Shin (CIPS) tests should be used. Nevertheless, if there is cross section independency, using LLC and IPS tests to check the stationary of variables is recommended.

The next step is to examine the evidence of a long-run relationship. The panel cointegration tests were employed to test the hypothesis of the existence of cointegration. To this end, Pedroni residual cointegration is utilized. In addition, to estimate the model using panel data, the regression relationship should be considered either in terms of the homogeneous intercept and the slope or the supposal of the same intercepts and the common gradient between the sections. To investigate such a case, the F-Limer test is used. If F-Limer indicates that panel data regression model is more appropriate than pooled data regression model, before the regression of the model, we use the Hausman test to determine whether to use the fixed effects model or employ the random effects model.

5. Results and Discussion

5.1. Descriptive Statistics

Descriptive statistics show that of 242 observations for the six variables used in our GMM model, natural gas consumption (LnNGASC) has the most variations around the mean (2.4), while natural gas price (LnNGASP) shows the least changes around the mean (0.8). Table 3 lists the descriptive statistics.

Table 3-Descriptive statistics of the variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
LnNGASC	242	13.397	2.412	8.8	17.8
LnPRO	242	9.178	1.611	5.9	13.0
LnENERIN	242	-2.146	1.041	-4.5	1.8
LnCO2EM	242	13.223	2.441	5.6	18.3
LnNGASP	242	5.872	0.829	4.9	6.9
LnAVPFF	242	6.732	1.327	4.6	8

Source: Current work findings

5.2. Cross Sectional Dependence (CD) Test

According to the results of CD test presented in Table 4, there is cross section dependency in error terms of the estimated model. This means that we cannot use LLC and IPS tests for performing panel unit root tests.

5.2. Unit Root Test

Since there is cross-section dependency in the panel data model, this paper utilized CIPS stationary tests to improve the reliability and validity of the results. The results of unit root tests of the model variables are presented in Table 5.

As tabulated in Table 5, the null hypothesis (homogeneous non-stationary) is rejected at the 1% or 5% level of significance, which means that, with the exception of the series of production (PRO) which are stationary in order one, I (1), all the other series are stationary in order zero, I(0), revealing that all the variables are integrated. Based on the given results of panel unit root tests, since variables are stationary in different cases, we can implement a panel cointegration test. Panel data cointegration tests proposed by Pedroni (1999, 2004) null hypothesis is joint non-cointegration.

Table 4- Cross section dependence test for profitability model

Test	Test statistics	Probability	Result
Pesaran's CD	6.678	0.000	Cross section dependency

Source: Current work findings

5.3. Pedroni Panel Cointegration Test

According to the panel unit root tests, we found that some variables are I(0) and one variable is I(1). Therefore, the next step is to test the evidence of a long-run relationship. To this end, Pedroni test was employed, and the results are as listed in Table 6.

Table 6 demonstrates that all the variables are cointegrated. Hence, Pedroni panel cointegration tests strongly support the existence of a long-run equilibrium relationships among the model variables. Therefore, the estimated regression is not a spurious regression. In other words, we can develop a significant regression model among the level of the variables. Next, we present the estimation results of the research model and its relevant discussion.

5.4. F-Limer and Hausman Test

The result of F-Limer indicates that the panel data regression model is more appropriate than the pooled data regression

Table 5 - CIPS unit root test results

Variable	Test Statistics	Result	Level
LnNGASC	-1.753**	stationary	I(0), Level
LnPRO	-2.054***	stationary	I(1), First difference
LnENERIN	-2.012***	stationary	I(0), Level
LnCO2EM	-1.946***	stationary	I(0), Level
LnNGASP	4.160***	stationary	I(0), Level
LnAVPFF	-2.203***	stationary	I(0), Level

Critical value of the 10%, 5%, and 1% level of significance is -1.53, -1.65, and -1.87 respectively.
Critical value of the first difference is -1.57, -1.72, and -1.98 at a 10%, 5%, and 1% level of significance respectively.
***, **, * denote the rejection of the null hypothesis at a 1%, 5%, and 10% level of significance respectively.
Source: Current work finding

Table 6 - Pedroni cointegration test

Series	Alternative hypothesis: common autoregresive (AR) coefficients (within-dimension)			
	Statistic	Probability	Weighted Statistic	Probability
Panel V-Statistic	-2.3790	0.991	-3.1602	0.999
Panel rho-Statistic	-5.8372	1.000	5.9248	1.000
Panel PP-Statistic	-2.5932	0.004***	-4.8743	0.000***
Panel ADF-Statistic	-1.5001	0.066*	-2.2737	0.012**
	Alternative hypothesis: individual AR coefficients (between-dimension)			
Group rho-Statistic	7.9629	1.0000		
Group PP-Statistic	-9.0659	0.000***		
Group ADF-Statistic	-2.2242	0.013**		

***, **, * denote the rejection of the null hypothesis at a 1%, 5%, and 10% level of significance respectively.
Source: Current work findings

model. Also, the Hausman test result illustrates that a fixed effect is preferred. The results F-Limer and Hausman tests are presented in Table 7.

5.5. Estimation and Analysis of the Model

This study estimated the dynamic panel data model by applying one-step Arellano-bond estimator based on GMM proposed by Arellano and Bond (1991). As proposed by the GMM two-step results, we should add the lagged dependent variables of natural gas consumption to Eq. (4), which are endogenous variables considering the fixed effects of industrial sectors; then, we can take the endogeneity for the lagged dependent variable of natural gas consumption in Iranian industrial sectors into account using GMM-type instruments. The estimations obtained by Eq. (4), along with the statistics and p-values of serial correlation tests, namely AR(1), AR(2), and Sargan test, are listed in Table 8.

Table 8 shows that the test statistics of the autocorrelation and validity of the instruments are satisfactory. The null hypothesis in the test for the first-order autocorrelation, AR (1), represents the existence of autocorrelation. In addition, the null hypothesis for the second-order autocorrelation, AR (2), shows no autocorrelation in the model. The test statistics of AR (1) and AR (2) are satisfactory, which is crucial to the validity of the instruments. The null hypothesis in the AR (1) test is rejected, it is accepted in AR (2). Moreover, the test statistics for the Sargan test regarding identifying restrictions (the validity of the instruments) is satisfactory; the null hypothesis is not rejected, so the Sargan test is robust.

Table 7- The results of F-Limer and Hausman tests

Test	Value	Probability	Result
F-Limer	43.02	0.000***	Panel Data
Hausman	194.64	0.000***	Fixed Effect

***, **, * denote the rejection of the null hypothesis at a 1%, 5%, and 10% level of significance respectively.
Source: Current work findings

As listed in Table 8, there is a positive relationship between the amount of natural gas consumption in Iranian industrial sectors and its first and second lags. In other words, the decision to use natural gas in Iranian industrial sectors can effect fuel consumption in the last two years because the manufactures were convinced to use more natural gas than the first year's capacity. In addition, the coefficients of the first and the second lagged value of natural gas consumption are significant at a 1% significance level. Accordingly, we estimated that, other things being equal, a 1% increase in natural gas consumption in the current year will on average lead to a 0.3912% rise in natural gas consumption in the next year; consequently, we estimated that, other things being equal, a 1% increase in natural gas consumption in the current year will on average result in a 0.1811% rise in natural gas consumption in next two years.

Another effective variable is Iranian industrial sector production (PRO) since the estimated coefficient of PRO has an important positive impact on NGASC at a 1% significance level. The estimation reveals that a 1% rise in PRO per year on average increases NGASC by 0.6050% in the Iranian industrial sectors during 2005 to 2015. This result is in line with empirical facts in the given sample data. Because more production needs more energy, this high coefficient shows that policymakers' environmental concerns lead industrial decision makers to use natural gas rather than the other sources of energy. To deal with this issue, policymakers adopted aligning policies to move towards a low carbon economy.

The results also reveal that energy intensity (ENERIN) has a positive and significant effect on natural gas consumption in industry section; on average, a 1% increase in energy intensity will approximately lead to a 0.42% increase in natural gas consumption in Iranian industrial sectors over the period studied, which proves the large effect of energy intensity on industrial sectors in the given sample data.

However, CO_2 emissions (CO2EM) has a positive sta-

Table 8 - GMM model results

GMM estimation; One-step Results						
Variable	Coefficient	Standard Error	Z	P > |Z|	[95% Confidence Interval]	
LnNGASC(-1)	0.3912	0.690	5.67	0.000***	0.2559	0.5265
LnNGASC(-2)	0.1811	0.0454	3.98	0.000***	0.0920	0.2702
LnPRO	0.6050	0.0679	8.90	0.000***	0.4717	0.7383
LnNGASP	-0.1453	0.1184	-1.23	0.220	-0.3774	0.0867
LnCO2EM	0.0825	0.0285	2.89	0.004**	0.0265	0.1385
LnAVPFF	0.1488	0.0869	1.71	0.087*	-0.215	0.3193
LnENERIN	0.4240	0.0533	7.95	0.000***	0.3195	0.5285
Number of observations	198					
Number of groups	22					
Number of instruments	58					
Arellano-Bond test for AR (1)	-2.6532 (Z)			0.000*** (Prob)		
Arellano-Bond test for AR (2)	-0.7399 (Z)			0.459 (Prob)		

***, **, * denote the rejection of the null hypothesis at a 1%, 5%, and 10% level of significance respectively.
Source: Current work findings

tistically significant but negligible effect on natural gas consumption. Totally, the estimation result shows that by assuming other conditions intact, a 1% increase in CO_2 emissions has made approximately more than a 0.08% positive impact on natural gas consumption in Iranian industrial sectors. The reason for this relationship is that there is an increasing rise in CO_2 emissions in Iran. Therefore, to reduce the amount of CO_2 emissions, policymakers prioritized restriction policies such as consuming clean fuels instead of polluting fuels.

Further, natural gas price (NGASP) has a negative but statistically insignificant effect on NGASC; it is estimated that, on average, a 1% rise in natural gas price will approximately lead to a 0.14% decrease in natural gas consumption in Iranian industrial sectors during the period studied. In fact, the results are in accordance with the pricing theory which indicates that an increase in the price of goods and services leads to decreased consumption.

Finally, the results demonstrate that the average of other fossil fuel price (AVPFF) has a positive significant effect on NGASC at a 1% significance level. Totally, the estimation result shows that, other things being equal, a 1% increase in the average of other fossil fuel price has approximately more than 0.1488% positive impact on natural gas consumption in Iranian industrial sectors.

6. Conclusions and policy implications

This research contributed to the stream of literature in the field of industrial sectors and sought to investigate and explore merely the influence of two types of environmental policies, namely price and non-price policies, on natural gas consumption and decreasing CO_2 emissions and energy intensity. Shifting from polluting fuels to clean and more reachable fuels such as natural gas has led the industrial sectors to similarly examine all the aspects of their environmental footprint and create strategies to become environmentally responsible and thrive in today's economic climate.

Thus, the implementation of appropriate policies is required in this context. Implementing price policies or non-price policies to manage natural gas consumption is the proposed solution to reducing environmental pollutions in Iranian industrial sectors. To this end, this paper investigated the effect of environmental policies, including price and non-price policies, on natural gas consumption in 22 Iranian industrial sectors during 2005-2015. Price-based environmental policies intended to utilize the prices of natural gas and other fossil fuels to direct Iranian industrial sectors towards using the clean fuel, i.e. natural gas. Since there are no clear non-price environmental policies to reduce pollution emissions, we used CO2 emission and energy intensity as proxies for these policies. We also considered the production of industry sector as a proxy to measure economic growth during the studied period.

Based on the empirical results, we concluded that there is a positive relation between the amount of natural gas consumption in Iranian industrial sectors and its first and second lagged during 2005-2015.

Furthermore, the estimation results indicated that energy intensity has a significant and positive impact on natural gas consumption in Iranian industrial sectors. The variable coefficient of energy intensity (non-price policy) has the greatest impact on the consumption of natural gas.

Another effective variable was Iranian industrial sectors' production (PRO). Since more production requires more energy, this finding confirmed the empirical facts. Nevertheless, this high coefficient revealed that the policymakers' environmental concerns lead industrial decision makers to use natural gas as a fuel instead of other sources of energy.

Moreover, the results revealed that there is a positive relationship between CO_2 emission and natural gas consumption. Thus, policymakers regulated the limitation policies through consuming natural gas instead of other fossil fuels to reduce the amount of CO_2 emission.

In accordance with the pricing theory, the average price of other fossil fuels had a positive significant effect on natural gas consumption, which indicated that a rise in the price of other fossil fuels increased the natural gas consumption. Further, natural gas price had a negative but statistically insignificant impact on natural gas consumption in Iranian industrial sectors.

Variables such as natural gas price and the weighted average of other fossil fuels represent price-based policies. In this study, the average weights of the price of other fossil fuels were represented as limitation tools to decrease polluting fuels such as gasoline, kerosene, fuel oil, gas oil, and liquid oil which have been used a lot between 2005 and 2015.

Overall, we found that the non-price environmental policies are more effective compared to price-based policies. Thus, we recommend that policymakers in Iranian industrial sectors should focus more on promoting energy efficiency through technological improvements and energy saving regulations.

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