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ESTIMATING INDUSTRIAL NATURAL GAS DEMAND ELASTICITIES IN SELECTED OECD COUNTRIES

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ABSTRACT

This study aims to estimate industrial natural gas demand in 15 selected OECD countries over the period of 1991 to 2016, within the framework of dynamic panel data model. The long-run income and own price and cross-price elasticities of natural gas in industry sector were computed by using fully modified OLS and dynamic OLS approaches as they have taken care of endogeneity by adding leads and lags (DOLS) or nonparametric approach to deal with serial correlation (FMOLS) in the presence or absence of cointegration. The results indicated that in FMOLS approach income elasticity spans from 0.08 to 0.21 and price elasticity was ranged between -0.05 to -0.07 (respectively in model with constant &trend and constant only). So demand is inelastic to price and income both. While in DOLS approach income elasticity was equal 0.63 and 1.15 and price elasticity was -0.14 and -0.51 in models with constant only as well as model with constant & trend respectively. Due to the price inelasticity of natural gas in the industrial sector, changing the price of natural gas or other substitutes does not lead to dipping the consumption and CO2 emission and levying taxes on natural gas price or other substitutes will not change the consumption habit in industry sector.

Contribution/ Originality: This paper's primary contribution is finding that if price increase by means of levying taxes on natural gas which is used as one of the main energy sources in the industry sector of the selected OECD countries will result in plunging the demand or curtailing CO2 emission.

1. INTRODUCTION

In 2016 global industry sector consumed 2754 million tonnes of oil equivalent of energy and OECD industries contributed to 29.9 percent of total energy use. Although, the share of natural gas in the energy mix of OECD countries was higher compared to the world (20 percent in the global level compared to 33 percent in OECD industries), industry sector of OECD countries consumed almost half of natural gas used in global industry sector. In 2016 (final year of the study), 49.9 percent of all natural gas consumption in the world industry sector allocated to OECD industries (IEA).

Consumption of natural gas in the OECD industry sector grew from 221 million tonnes of oil equivalent in 1991 to 264 million tonnes of oil equivalent in 2016.Industry sector contributed to 21.5 percent of energy consumption in OECD countries and natural gas accounts for 33 percent of the energy mix in this sector in 2016 up from 27 percent in 1991. In 2016 share of natural gas consumption in industry sector was 35.9 percent of total consumption in the economy (IEA). Figure 1 demonstrates the aggregation of natural gas consumption in the

OECD industry sector in million oil equivalent. It shows that natural gas consumption has increased during the time.

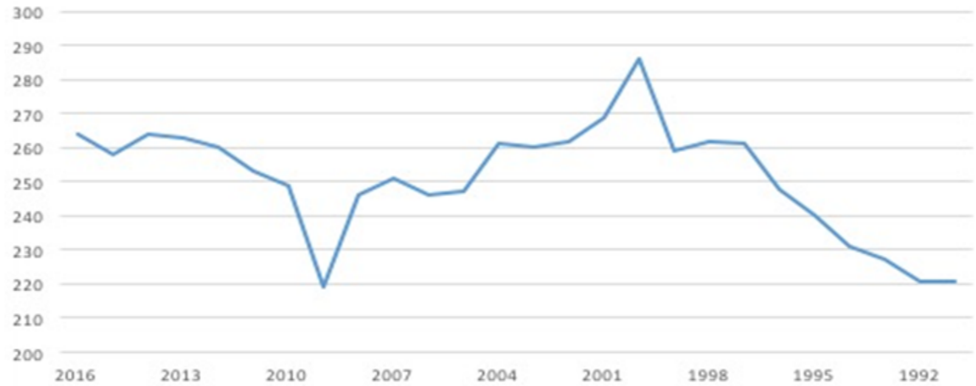

Figure-1. Natural gas consumption in OECD industry sector (million toe).

Source: IEA.

From 1991 to 2016, share of natural gas consumption in the OECD industry sector rose 6 percent and reached 33 percent, which was the highest increase rate among all other energy sources. On the other hand biggest decrease in share of energy sources was seen in oil product consumption. In 1991 around 20 percent of energy used in the OECD industry sector came from oil products, but in 2016 oil products contributed to 11 percent of all energy consumption. Figure 2 depicts share of each source of energy in the industry sector of OECD countries.

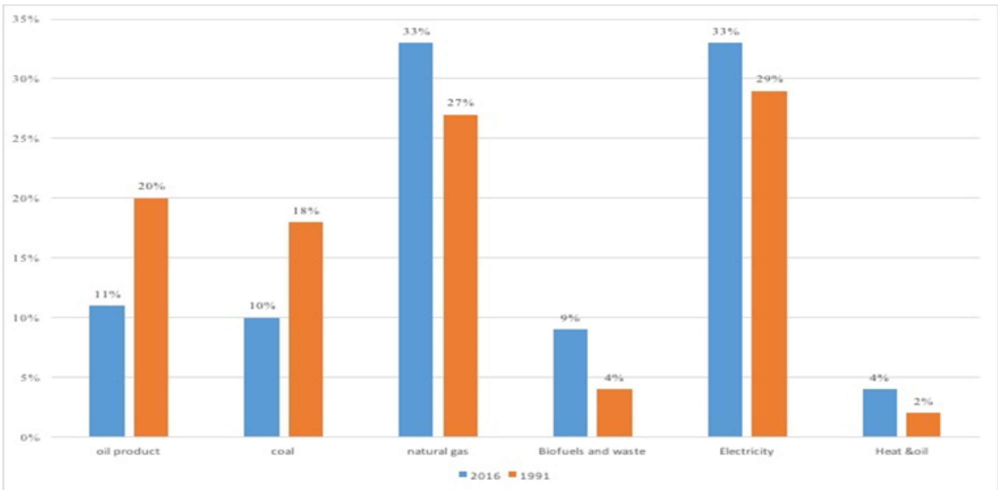

Figure-2. Share of each sources of energy in OECD industry sector consumption (percent).

Source: IEA.

Based on IEA report, burning natural gas for energy results in fewer emissions of nearly all types of air pollutants and carbon dioxide (CO_2) than burning coal or petroleum products to produce an equal amount of energy. About 117 pounds of carbon dioxide are produced per million British thermal units (MBtu) equivalent of natural gas compared with more than 200 pounds of CO_2 per MBtu of coal and more than 160 pounds per MBtu of distillate fuel oil. The clean burning properties of natural gas have contributed to increased natural gas use for electricity generation and as a transportation fuel for fleet vehicles in the United States. In figure 3, the CO_2 emission of different sources of energy during burning is shown.

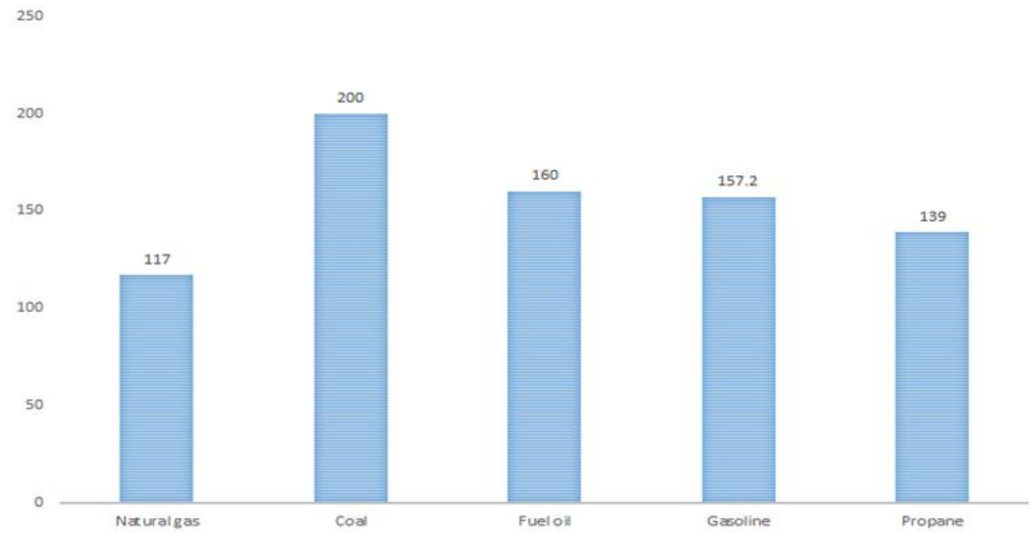

Figure-3. Pounds of CO_2 emitted per million British thermal units (MBtu) of energy for various fuels.
Source: IEA.

As it is depicted in Figure 3, by considering the emission of CO_2 in the process of burning natural gas, it cannot be considered a clean energy source, only it can be named cleaner fossil fuel energy compared to coal and oil (IEA). So, in order to combat CO_2emission which has a severe impact on the environment and caused many problems like global warming and encourage industries to change technologies and infrastructures and use environment-friendly technologies, it is essential to use clean energy like solar, wind and other renewable energies and reduce consumption of natural gas as well as other fossil fuels (Global energy and CO_2 status report).

In this paper modelling long-run industrial energy demand and understanding the determinants behind it is the main purpose. It can give insight about policies that can be useful and have a big impact on the consumption decision in big industries.

As a result, in this paper price and income elasticities of natural gas demand are estimated and the cross-price elasticity of natural gas and substitute energy resources will be calculated to better understand the reactions of demand function to price or income change. Finding these elasticities is necessary when trying to predict future demand for energy as well as when forming energy or environmental policy to combat CO_2 emission (Adeyemi and Hunt, 2007).

The paper is organized as follows. Section 2 covers Literature review and section 3 presents data and methodology and a discussion of the results is in section 4 followed by a conclusion in section 5.

2. LITERATURE REVIEW

In terms of modeling natural gas demand, different classifications have been used. Natural gas is one of the burning fuels in different economic sectors including industry, residential, transport and power. Due to less polluting characteristics of natural gas, its consumption has risen during past years.

All types of studies can be classified as follows:

The first: During the last 20 years, some of the studies focus on the aggregation of natural gas consumption in the whole economy. Some of the notable studies of natural gas demand in the whole economy in a time period are Eltony (1996), Asche *et al.* (2008), Burke and Yang (2016).

Some of the empirical studies of demand for natural gas are shown in Table 1.

The second: Studies of energy demand in whole economy or different economic sectors. In this group of studies all kinds of energy for the whole economy has been considered not one type of energy source.

The third: Studies that focused on different sectors of the economy (Joutz (2008), Narayan *et al.* (2007); Adeyemi and Hunt (2007)).

The fourth: studies that used the FMOLS and DOLS approach to estimate the demand function and the most notable ones are the studies done by Bilgili (2013) and Lee (2005).

Some of the empirical studies focusing on natural gas demand function, covering all last three classifications of study, are shown in Table 2.

Table-1. Modeling natural gas demand.

	Elasticity					
Author	**Price**	**Income**	**Period**	**Country**	**Sector**	**Method**
Nilsen *et al.* (2005)	-1.541 to 1.844	1.649 to 2.251	1978-2002	12 European	Economy	OLS,GLS,SUR,2SLS
Eltony (1996)	-0.17	0.48	1975-1993	GCC	Economy	Error component model(ECM)
Yoo *et al.* (2009)	-0.226	0.496	2005 (380 obs)	South Korea	Residential	Univariate model
Yoo *et al.* (2009)	-0.243	0.335	2005(380 obs)	South Korea	Residential	Bivariate model
Bernstein and Madlener (2011)	-0.51	0.94	1980-2008	OECD	Residential	ARDL
Burke and Yang (2016)	-1.25	+1	1978-2011	44 Countries	Economy	IV
Lim (2019)	0.57	1.48	1998-2018	south korea	Residential & industrial	Kalman filter
Fung *et al.* (1999)	-0.904 to -2.51	-0.005 to 0.009	1993(daily)	Canada	Residential	FMOLS and DOLS
Bilgili (2013)	-0.345 -0.318	-0.318 1.329	1979-2006	8OECD	Economy	FMOLS DOLS

Table-2. Modeling energy demand.

	Elasticity					
Author	**Price**	**Income**	**Period**	**Country**	**Sector**	**Method**
Bentzen and Engsted (1993)	-0.465	1.213	1993	Denmark	Economy	Co-integration and error-Correction method(ECM)
Al-Rabbaie and Hunt (2006)	-0.4	1.5	1960-2003	17 OECD	Economy	structural time series(STSM)
Adeyemi and Hunt (2007)	-0.22	0.8	1962-2003	15 OECD	Industrial	Non-linear least squares
Galindo (2005)	below -0.5	0.96	1965-2001	Mexico	Transport, residential, industrial & agriculture	Co-integration approach
Liu (2004)	-0.5	0.96	1965-2001	23 OECD	residential, industrial &transport	Difference GMM
Hunt and Ninomiya (2005)	-0.2	1.5	1887-2001	Japan	Economy	ARDL
Liddle (2017)	-0.11 to - 0.28	0.22 to 0.70	1987 - 2013	50 states in USA	Economy /residential Industrial/transport	DCCE
Narayan *et al.* (2007)	-1.45 to -1.53	0.245 to 0.312	1978-2003	G7	Residential	Difference GMM

Lee (2005) used the data for 18 developing countries from 1975 to 2001 to reinvestigate the causal relationship between energy consumption and GDP and used FMOLS approach to estimate the long run relationship. Bilgili (2013) has estimated the long run elasticity of demand for natural gas in 8 OECD countries and in the whole economy. Price and income elasticity of natural gas in the whole economy was -0.345 and 1.329 respectively by using FMOLS approach. In this paper we are using FMOLS and DOLS approach to estimate natural gas demand function in industry sector. In this paper larger number of countries and wider time span is used.

The purpose of this paper is to investigate the long-run price and income elasticity of natural gas in the industry sector of developed countries. Most of the previous studies have focused on the whole energy elasticity or natural gas elasticity in the whole economy or residential sector.

Industry sector is a main consumer of natural gas in the economy. Due to less polluting characteristics of natural gas, it is going to have a bigger share in industry sector as an energy source (IEA) so studying this relationship can be useful for industrial and environmental policy making.

3. METHODOLOGY, THEORY AND DATA

3.1. Theory

In order to derive the demand function for natural gas in the industrial sector, consider the profit function. Firms try to achieve maximum economic profits and choose their input and output in a way that the difference between the total revenues and total economic costs is as large as possible.

As it is written in the Equation 1, the profit function is the difference between the revenue ($P_t\ Q_t$) and the total cost of production (TC) that should be maximized.

$$Profit\ =\ P_t Q_t - \lambda\,(C_t + P_{Kt}K_t + P_{Lt}L_t + P_{gt}NG_t + P_{st}SUB_t) \qquad (1)$$

Where:
P: price.
Q: production.
K: capital stock.
L: labour.
NG: natural gas.
SUB: substitute energy sources for natural gas (electricity and fossil fuels).

The contingent demand function for any input including natural gas can be derived by using Shephard's lemma. This is done by differentiating the cost function with respect to the factor prices resulting in the partial derivatives. Equation 2, shows the natural gas demand function in the industry sector, which is derived by partial differentiating the profit function.

$$NGD = f\,(P_g, P_s, Q) \qquad (2)$$

Following Espey (1996), Alberini and Filippini (2011) and Santos (2013) energy demand is expressed as a function of price and value added. So, as presented in Equation 3, the final model for natural gas demand is as follows:

$$NGD = f\,(P_g, P_s, VA) \qquad (3)$$

As fossil fuels are one of the main sources of energy in power plants, the price of electricity is highly collinear with the price of fossil fuel substitutes so the ratio of the two prices is introduced as an explanatory variable in the model (Kennedy, 2002).

3.2. Cross-Section Independence

Phillips and Sul (2003) show that if there is a sufficient cross-sectional dependence in the data and this is ignored in estimation, decrease in estimation efficiency can become so large that using pooled least square estimator may provide little gain over the single equation OLS (De Hoyos and Sarafidis, 2006).

The Lagrange multiplier (LM) test, developed by Breusch and Pagan (1980) can be employed when the time dimension (T) of the panel is larger than the cross-sectional dimension (N) (as in our case N is 15 and T is 25).

The test is based on this LM statistic which is presented in Equation 4:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \qquad (4)$$

In Equation 4, $\hat{\rho}_{ij}$ shows a sample estimate of pairwise correlation of residuals and the LM statistics is asymptotically distributed as chi-squared with $N\,(N-1)/2$ degrees of freedom.

The Null hypothesis to the Breusch and Pagan (1980) test for cross-sectional independence is followed:

$$H_0 = COV(u_{it}, u_{jt}) = 0 \;\; for\ all\ t\ and\ i \neq j$$

The alternative hypothesis is as follows:

$$H_1 = COV(u_{it}, u_{jt}) \neq 0 \;\; for\ at\ least\ one\ pair\ of\ i \neq j$$

The bias-adjusted version of the LM test developed by Pesaran *et al.* (2008) Pesaran cross sectional dependence (CD), and Baltagi, Feng and Kao bias corrected scaled LM are used too. However Pesaran CD is regarded as the most general one as it is suitable for stationary and non-stationary panels and consists of reasonable small sample properties.

3.3. Unit Root Test

Panel unit root tests categorized as "First generation" and "Second generation. In "second generation tests" cross sectional dependency taken into account and if it is found that there is a cross section dependency in the model the second generation should be used. Most notable second generation test is CIPS, which was proposed in 2007.

For a panel of observed data with N cross-sectional units and T time series observations, the dynamic linear heterogeneous model is written in Equation 5:

$$Y_{i,t} = (1-\delta_i)\mu_i + \delta_i Y_{i,t-1} + u_{i,t}, \qquad (5)$$

$$i = 1, \ldots\ldots, N,$$

$$t = 1, \ldots\ldots\ldots, T,$$

With given initial values $Y_{i,0}$ and one factor structure for the disturbance

$$u_{i,t} = \lambda_i f_t + e_{i,t} \qquad (6)$$

In Equation 6, by considering serially uncorrelated disturbances, the idiosyncratic components $e_{i,t}$ are assumed to be independently distributed both across $i\ and\ t$. In Equation 6, the idiosyncratic components $e_{i,t}$ have zero mean and variance equals σ_i^2 and finite forth-order moment. The common factor f_t is serially uncorrelated with mean zero and constant variance σ_f^2 and finite forth-order moment. Without loss of generality σ_f^2 is set equal to one and $e_{i,t}$, λ_i , f_t are assumed to be mutually independent for all $i\ and\ t$.

In this case the model can be rewritten as Equation 7 which is based on Equations 5 and 6:

$$\Delta Y_{i,t} = \alpha_i - (1-\delta_i)Y_{i,t-1} + \lambda_i f_t + e_{i,t} \qquad (7)$$

In Equation 7, $\alpha_i = (1-\delta_i)\mu_i$ and $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$. (Pesaran, 2007)

The null hypothesis is $\delta_i = 1$ for all i and the alternative hypothesis is $\delta_i < 1$

For the unit root null hypothesis considered by Pesaran (2007) he proposes a test based on the t-ratio of the OLS estimates $\hat{b}_i$ in the following cross-sectional augmented DF (CADF) regression which is depicted as Equation 8.

$$\Delta Y_{i,t} = a_i + b_i Y_{i,t-1} + c_i \bar{Y}_{t-1} + d_i \Delta \bar{Y}_t + \epsilon_{i,t} \qquad (8)$$

In Equation 8, there are some confirmed assumption which are as follows: $\bar{Y}_t = \frac{1}{N}\sum_{i=1}^{N} Y_{i,t}$, $\Delta\bar{Y}_t = \sum_{i=1}^{N} \Delta Y_{i,t}$,

$\epsilon_{i,t}$ is the regression error.

The cross-sectional averages, $\bar{Y}_{t-1}$ and $\Delta\bar{Y}_t$ are included in the Equation 7 as a proxy for the unobserved common factor f_t. CADF is a bootstrap method for the covariates augmented Dickey-fuller and uses related variables to improve the power of the univariate unit root test and the CIPS statistics is computed as group-mean of t- statistics obtained from particular CADF equations (Pesaran, 2007)

Computation of test statistics and inference is the same as IPS procedure which is shown in Equation 9:

$$\text{CIPS}=\frac{1}{N}\sum_{i=1}^{N} CADF_i \qquad (9)$$

3.4. Panel Cointegration Test

As cross-sectional dependence between variables are confirmed and all are I (1), the cointegration analysis that was proposed by Westerlund and Edgerton is applied. Westerlund (2007) cointegration test considers cross-sectional dependence and structural breaks simultaneously.

Westerlund test is based on the error correction model that is written in Equation 10.

$$\Delta y_{it} = \delta_i' d_t + \alpha_i\left(y_{i,t-1} - \beta'_i x_{i,t-1}\right) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij}\, \Delta x_{i,t-j} + u_{it} \qquad (10)$$

In Equation 10, both i=1,…….,N and t=1,……, T represent cross section and time series, respectively and d_t is deterministic components and α_i is the error correction term.in equation 10, p_i *and* q_i are the number of lags and leads, respectively. The first sum corresponds to standard lagged differences account for short-run adjustment dynamics. If α_i < 0, then there is error correction and y_{it} *and* x_{it} are cointegrated.

If $\alpha_i = 0$ in equation 10, then the error correction will be absent and there will be no long run equilibrium equation (Christophe and Llorca, 2017).

Westerlund (2007) test consists of four tests, two of them are group mean statistics (G_t and G_a) and two are panel statistics (P_t and P_a). Westerlund (2007) proposes that error correction tests, have better size accuracy (good small sample properties) and higher power compared to the residual based tests of Pedroni (2004). The null hypothesis for all tests is $\alpha_i = 0$ for all I which means no cointegration in all countries.

The alternative hypothesis for G tests are α_i<0 for at least one i which means cointegration at least in one country and the alternative hypothesis for P tests are α_i<0 for all i which means cointegration in the whole panel (Westerlund, 2007). Westerlund approach accounts for cross-sectional dependency by using bootstrapping to compute the errors (Persyn and Westerlund, 2008). Monte Carlo estimation carried out by Westerlund (2008) show that First panel tests have the highest power, and second among the group mean statistics, G_t has the highest power.

Following Lee (2005) in the presence of unit root variables if OLS is employed, the effect of superconsistency may not dominate the endogeneity effect of the regressors. Pedroni (2000) showed that in the FMOLS setting, nonparametric techniques are used to transform the residuals from the cointegration regression and get rid of nuisance parameters. So FMOLS can be modified to make an interference in being cointegrated with the heterogeneous dynamic. DOLS approach uses leads and lags to take care of endogeneity problem.

3.5. FMOLS and DOLS Models

In order to estimate the long run panel coefficients of the model panel FMOLS and DOLS is used. To calculate the parameters of these models, it is required to decompose a long run covariance matrix Ω as defined in Kao *et al.* (2002) and it is shown in Equation 11.

$$\Omega = \sum_{j=-\infty}^{\infty} E\left(\psi_{ij}\psi'_{i0}\right) = \begin{bmatrix} \Omega_\mu & \Omega_{\mu\varepsilon} \\ \Omega_{\varepsilon\mu} & \Omega_\varepsilon \end{bmatrix} \quad (11)$$

In Equation 11, $\psi_{it} = (\mu_{it}, \varepsilon'_{it})'$.

The symmetric, or one-sided covariance matrix is defined as in the Equation 12:

$$\Pi = \sum_{j=0}^{\infty} E\left(\psi_{ij}\psi'_{i0}\right) = \begin{bmatrix} \Pi_\mu & \Pi_{\mu\varepsilon} \\ \Pi_{\varepsilon\mu} & \Pi_\varepsilon \end{bmatrix} \quad (12)$$

As Kao and Chiang (1998), Pedroni (2001) and Basher and Mohsin (2004) explained, the estimators of fully modified OLS (b_{fm}) and dynamic OLS (b_{dols}) can be calculated by using Equations 13 and 14:

$$b_{fm} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - \bar{X}_i)^2\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - \bar{X}_i)(\hat{Y}_{it}^{*} - T\hat{\Pi}_{\varepsilon\mu}^{*})\right) \quad (13)$$

In Equation 13, $\hat{Y}_{it}^{*} = Y_{it} - \hat{\Omega}_{\mu\varepsilon}\Omega_\varepsilon^{-1}\varepsilon_{it}$ and $\hat{\Pi}_{\varepsilon\mu}^{*} = \hat{\Pi}_{\varepsilon\mu} - \hat{\Pi}_\varepsilon\hat{\Omega}_\varepsilon^{-1}\hat{\Pi}_{\varepsilon\mu}$

$$b_{dols} = N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} Z_{it}Z'_{it}\right)^{-1}\left(\sum_{t=1}^{T} Z_{it}\hat{Y}^{*}_{it}\right) \tag{14}$$

$Z_{it} = (X_{it} - \bar{X}_i, \Delta X_{it-k}, \dots \dots \dots, \Delta X_{it+k})$ is 2 (K+1)$\times 1$ vector of explanatory variables under the panel DOLS regression as depicted by Equation 14.

As explained by Kao and Chiang (2000) b_{fm} *and* b_{dols} are obtained under a homogeneous covariance matrix. Kao and Chiang (2000) and Pedroni (2001) showed that these estimators can be estimated under a heterogeneous covariance matrix. b_{fm} *and* b_{dols} follow asymptotically normal distribution with 0 means but the former estimator corrects the endogeneity and serial correction in b_{dols} Kao and Chiang (1998) but the latter estimator which is b_{dols} is obtained from an augmented form of OLS equation in which lead and lagged differences are taken in order to control for endogeneity in the panel data set (Pedroni, 1996; Kao and Chiang, 1998; Holmes, 2006).

3.6. Data

In this paper, 15 OECD countries, including the United States of America, United Kingdom, France, Germany, Austria, Poland, Canada, New Zealand, Czech Republic, Finland, Spain, Italy, Switzerland, Turkey, Japan, are observed from 1991 to 2016 and the selection was based on the availability of data for the variables used in the model.

Data for natural gas consumption in the industrial sector, including construction, is collected from IEA.org in million tonnes of oil equivalent (NGD). Data for industry value added (VA) including construction in million U.S dollars are available on the world bank website and the price of all three energy resources (coal, natural gas and diesel fuel for industry sector) is available on the 'IEA energy prices and taxes" reports for the years 1999, 2005, 2017 as well as Eurostat and all the prices are in U.S dollars per tonne of oil equivalent.

The natural gas price for industry sector (Pg) and the ratio of fossil fuel prices (including the weighted average of coal and diesel fuel used in industry sector) and electricity price in the industry sector, denoted as the price of substitute fuel (Ps), is explanatory variables. In the paper, U.S GDP deflator for the year 2010 is used to covert current prices to constant price of 2010.

4. RESULTS

We applied above mentioned methodology to the strongly balanced panel dataset. All variables are transformed in natural logarithmic terms before analysis.

Firstly, the tests for analyzing cross-section dependency in panel dataset is used. Although, there are different tests for detection of cross-section dependency in the literature, but Breusch and Pagan (1980), Pesaran (2004), Pesaran (2004) and Baltagi *et al.* (2012) bias-corrected scaled LM which are the most frequently used tests are applied and the results are presented in Table 3. Results of all four tests on all four variables indicated the strong presence of cross sectional dependency. This implies that any shock in industrial natural gas market occurs in any country affects other countries.

Table-3. Cross-section dependence tests.

Tests/Variables	NGD	VA	P_g	P_s	Model
Breusch-pagan LM	918.25(0.000)	1189.34(0.000)	1231.58(0.000)	600.46(0.000)	987.83(0.000)
Pesaran Scaled LM	56.12(0.000)	74.82(0.000)	77.74(0.000)	34.19(0.000)	60.92(0.000)
Biased-corrected Scaled LM	55.82(0.000)	74.52(0.000)	77.44(0.000)	33.89(0.000)	60.62(0.000)
Pesaran CD	2.19(0.028)	25.14(0.000)	29.69(0.000)	8.31(0.000)	3.76(0.000)

Note: Null hypothesis: No cross-section dependence. The statistics in parenthesis are P-value. All the tests were significant at 1 percent.

In the presence of cross section dependency the first generation of unit root tests cannot give valid results and the second generation should be applied. In Table 4 the results of unit-root panel test of Pesaran (2007) is presented and based on the statistics all the variables except the price of substitutes in the presence of constant and time trend are nonstationary at level. However, the CIPS test rejects the null hypothesis of nonstationity at the 1%level when the variables are transformed in first difference.

So all of them are cointegrated of order 1. All the mentioned results lead us to examine whether the variables are cointegrated in panel perspective or not.

Table-4. Pesaran (2007) panel unit root test (CIPS).

Variables	Variables in level		Variables in first difference	
	Constant	Constant & trend	Constant	Constant & trend
NGD	-1.480	-2.599	-4.763***	-4.951***
VA	-1.761	-2.143	-4.440***	-4.572***
P_g	-2.833	-2.70	-5.080***	-5.116***
P_s	-1.963	-3.068	-5.093***	-5.424***

Note: critical values for CIPS test with constant only are -2.45 for 1% significance, -2.25 for 5% significance and -2.14 for 10% significance. The critical values for CIPS test with trend and constant are -2.96 for 1% significance, -2.76 for 5% significance and -2.66 for 10 percent significance and the Null hypothesis in CIPS test is the panel is homogenous non stationary. *** statically significant at 1% level.

The best cointegration test available when there is a cross section dependency in the model is Westerlund test. To consider cross sectional dependency, the robust p-values that are generated through bootstrapping is estimated.

Table 5 shows the results of Westerlund test. As shown in the Table 5 G_t and G_a tests provide evidence of slope heterogeneity at the 1% level of significance and by considering the results of P_t and P_a tests, we can reject the null hypothesis of no conitegration and accept there is cointegration at least in some panels (the alternative hypothesis)

Table-5. Results of Westerlund cointegration tests.

Statistics	Without constant and trend			Constant only			With constant and trend		
	value	p-value	Robust p-value	value	p-value	Robust p-value	value	p-value	Robust p-value
G_t	-3.238	0.000	0.000	-0.071	0.472	0.053	-2.898	0.194	0.023
G_a	-5.960	0.874	0.005	2.589	0.995	0.105	-7.592	1.000	0.025
P_t	-27.537	0.000	0.000	-14.553	0.000	0.000	-37.427	0.000	0.000
P_a	-11.182	0.000	0.000	-3.285	0.001	0.000	-26.258	0.000	0.000

Note: G_t and G_a are the group-mean statistics and P_t and P_a are the panel statistics. The null hypothesis is no cointegration for all countries in the panel. The Robust P-values are for one sided test based on the bootstrapped distribution. We use 400 bootstrap replications. The bootstrapped version of the error correction tests is robust to the presence of cross-section dependence. To estimate the panel cointegration model we chose 2 lags and 0 leads for each series and the Bartlett kernel window set to $4\,(T/100)^{\frac{2}{9}} \approx 3$.

As the presence of cross-sectional dependence confirmed by tests so inference based on the asymptotic normal distribution is inadequate and the inference must be based on the Robust P-values that are generated through bootstrapping to account for the cross section dependence.

The results from the robust P-values show that, except for the G_a test (in two cases: a constant only and both constant and trend), all the tests concludes the rejection of the null hypothesis of no contegration. Based on the results, all the panel tests reject the null hypothesis of no cointegration at 1% significance level and majority of groups-mean test statistics reject the null hypothesis of no cointegration. So we conclude that all the variables in the model are cointegrated and have long run associationship and in the next step we have to estimate the coefficients. Table 6 shows the result of FMOLS and DOLS estimation and the long-run estimates of variables.

Table-6. Estimation of long-run coefficients.

	FMOLS		DOLS	
Variables	**Constant only**	**Constant & trend**	**Constant only**	**Constant & trend**
VA	0.21(3.37)**	0.08(2.69)**	0.63(5.40)***	1.15(4.23)***
p_g	-0.07(-3.05)**	-0.05(-3.20)**	-0.14(-3.93)***	-0.51(-2.79)***
p_s	0.00(0.53)	0.01(6.45)***	0.14(1.13)	0.33(1.79)**

Note: to estimate the coefficients in DOLS approach 3 lags and no leads is selected. For lrcov options in FMOLS approach vlag(1) and vic(aic) is selected. Numbers in parenthesis are t statistics. * shows 0.1percent, ** shows 0.05 percent and *** shows 0.01 percent significance.

FMOLS estimation has the purpose of eliminating the nuisance parameters of the dependant variable through using long run covariance matrices and DOLS estimation has the purpose of reaching appropriate statistical limiting distribution through corrections of the nuisance parameters by leads and lags. So after corrections of FMOLS and DOLS there won't be the problem of endogeneity and serial correlation in the model (Kao *et al.*, 1999).

Based on the results, all the coefficients except for the coefficient of substitute energy resources in the models without trend are significant at either the 1 percent level or 5 percent level based on the t- statistics and all of them have the expected signs. As all the variables are in logarithmic form, all of them can be interpreted as the elasticities in natural gas demand function in the OECD industry sector. The income elasticity of natural gas in industrial sector in FMOLS is either 0.21 (model with constant only) and 0.08 (model with constant and trend) which shows that natural gas price is inelastic to income but by using DOLS approach the income elasticity increases and it will be either 0.63 or 1.15. In case of evaluating the model without trend, industrial natural gas demand is inelastic to income and 1 percent increase in value added of industry sector cause the demand to rise just 0.63 percent, but in the presence of trend the situation changes and 1 percent rise in industry value added cause the demand to grow by rate of 1.15. In this case natural gas demand is elastic to income.

The price elasticity of natural gas in industrial sector in FMOLS approach is between 0.05 to 0.07 percent, which is very low and the sign confirmed that any growth in the price decreases the demand at a very slow rate. In DOLS estimations the price elasticity is in the range of 0.14 to 0.51, meaning that natural gas in the industrial sector is inelastic to price change and the sign of price elasticity is aligned with the theory.

On the other hand the cross- price elasticity in FMOLS model with constant and trend is just 0.01 which can be interpreted as no change in natural gas demand in the industry sector in case of change in the price of substitute energy resources and in the DOLS estimation with trend and constant it is 0.33.

The cross- price elasticity in both estimation and with the presence of constant only are insignificant.

These results, show that natural gas demand in the industrial sector of OECD countries is insensitive to changes in the price of either natural gas or other energy resources. Besides, except in one case (DOLS approach with constant and trend) natural gas demand in the OECD industry sector is inelastic to income change too.

5. CONCLUSION AND POLICY IMPLICATION

We examined the long-run determinants of industrial natural gas demand in 15 OECD countries during 1991 to 2016 and the majority of the results indicate that natural gas demand in industry sector is inelastic to price and income as the elasticities are lower than 1 (except in the case of DOLS model with trend and constant), but in all 4 estimations the income elasticity is higher than price elasticity and the own price elasticity is higher than cross-fuel price elasticity.

The price inelasticity of natural gas in OECD industry sector indicates that rising natural gas prices in the future will not reduce its consumption and just results in extreme inflation. Decreasing the price of electricity or coal for industry sector will not tumble industrial natural gas demand as the demand function is inelastic to price of substitutes.

Furthermore, the implementation of pricing policies to curtail natural gas use in industry sector may not be useful, due to the relatively low magnitude of price elasticity.

Low income elasticity indicates that even increase or decrease of industrial value added does not have a significant effect on natural gas demand, so policies that aims to tax the revenue of the industry cannot affect their decision about natural gas consumption.

Besides infrastructure and technologies used in the industry sector are so expensive and changing energy price may not lead to changes in technologies or facilities used in this sector.

This signals that governments should find new mechanisms to modify consumption patterns either by policies that affect consumption decisions like informing them about the result of their consumption decisions on environment, or subsidizing the installation of more energy efficient technologies. A new regulation that encourages industries to invest in cleaner technologies can be an option.

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