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The Effects of Climate and Oil Prices on Residential Natural Gas Prices: With an Application to 11 OECD Countries

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Abstract
This study examines the effects of climate and oil prices on residential natural gas prices in selected 11 OECD countries by using panel data for the period 1992-2016. After applying the panel unit root tests, the parameters are estimated using Common Correlated Effects Pooled (CCEP) method. Moreover, Emirmahmutoglu-Kose (2011) test is used to test the panel causality between the variables. The results revealed that in the long run, the heating degree days have a statistically significant and negative effect on natural gas prices used in the residential sector in selected OECD countries, while there is an insignificant relationship between oil prices and natural gas prices used in the residential sector in these countries. It is also found to be a causality of heating degree days to natural gas prices.

Keywords
climate, natural gas prices, growth, common correlated effects pooled, Emirmahmutoglu-Kose causality test.

Introduction

US Energy Information Administration (EIA, 2018) collects the factors affecting natural gas prices under two main headings. The first one is the supply-side factors that affect prices (amount of natural gas production, natural gas level in storage, natural gas import and export volume), and the second one is demand-side factors (changes in weather conditions in winter and summer seasons, level of economic growth, availability and price of substitute fuels). Szoplik (2015) stated that natural gas consumption depends on external factors. He listed these factors as a calendar (weekday, daytime, month, season), weather (temperature, humidity, sun, wind speed), demographic characteristics (general population, the number of households and children, birth rate), economic (GDP, the price of natural gas) and building characteristics (type of property, type of building, size of building area, substance/strength of window pane, type of roof). These factors have been found to have an effect on natural gas consumption in several studies (Villar and Joutz, 2006; Timmer and Lamb, 2007; Brown and Yücel, 2008; Harold et al., 2015). Consequently, changes in these factors may affect the consumption and price of natural gas.

This study focuses on the effects of changes in heating degree days (HDD) and prices of oil, which is a substitute fuel for natural gas, on prices of natural gas. Unexpected changes in weather conditions will affect the natural gas demand for both residential and commercial consumers. Changes in natural gas demand may trigger changes in its price. On the other hand, increases and decreases in the cost of substitute fuels (e.g. oil prices) may lead to increases and decreases in demand and price of natural gas. Erdogan (2010) analyzed the price elasticity of demand for natural gas in Turkey and revealed that this elasticity is quite low. Accordingly, he states that consumers in Turkey have not reacted to possible price increases by reducing their demands for natural gas or substituting it with other energy sources. Zhang et al. (2018) investigated the price and income elasticity of demand for natural gas in different sectors in China. They concluded that the price elasticity of demand for natural gas in sectors other than the residential sector is greater than 0 in the long run. Burke and Yang (2016) estimated the long-run price and income elasticity of demand for natural gas in 44 countries from the period 1978-2011. In this study, the price elasticity of demand for natural gas is estimated to be around -1.25, while the income elasticity of demand for natural gas is estimated to be more than 1. According to Tol et al. (2012), energy has been a luxury good for low-income households, a necessity good for middle-income households, and a saturated good for households with higher incomes. They also stated that there is a simple and linear relationship between energy prices, climate, and income. On the other hand, Lee and Chiu (2011) stated that in low-income countries, the temperature rise would decrease electricity consumption while the temperature rise in high-income countries would increase it. They also concluded that there is a non-linear relationship between electricity consumption, real income, electricity price, and temperature.

Mansanet-Bataller et al. (2007) stated that both hot and cold days would cause abnormal and positive price changes. While the use of energy for heating in extreme cold weather is higher, the increase in energy use in extreme heat will result from a leap in the use of air conditioning. Villar and Joutz (2006) discussed that cold weather increases the demand for natural gas for heating, and such an increase in demand for natural gas also triggers its price to increase. They also argued that because international supply and demand shocks affect crude oil markets and relative domestic demand, such shocks and the weather could also influence the natural gas markets.

Significant changes in oil prices are one of the main reasons that pave the way for significant economic changes. In other words, changes in oil prices can create important effects on several economic indicators (economic growth, inflation, foreign trade, etc.). More specifically, changes in the long-term oil prices trigger the changes in natural gas prices in general (Müller et al., 2015; Çelik and Barak, 2018).

The International Energy Agency (IEA, 2017) stated in its "GAS 2017" report that the natural gas market is expected to grow faster than oil and coal markets in the next five years due to its low price, supply with faster face when compared to rival fuels, and role in reducing air pollution and emissions. IEA (2017) also predicted that the demand for natural gas would increase by 1.6% per annum by 2022. As a result, natural gas consumption, which was 3630 billion cubic meters (bcm) in 2016, will reach approximately 4000 bcm as of 2022. As shown in Figure 1, the natural gas consumption in OECD countries was 1465.2 bcm in 2007, while it has increased to 1677.6 bcm as of 2017. Not only consumption but also the production of natural gas production has increased during this period. However, such an increase in production cannot meet the demand for natural gas. Dilaver et al. (2014) also argued that because natural gas has a lower carbon density and higher fuel efficiency compared to other fossil fuels, it will continue to strengthen its presence in the fuel market.

This study, which examines the effects of climate and oil prices on residential natural gas prices in selected 11 OECD countries by using panel data for the period 1992-2016, is structured as follows. In the following second section, the relevant literature is reviewed. In the third section, the material and the method of the study are described, while the findings obtained by application of relevant tests are covered in the fourth section. In the fifth section, the study was concluded by discussing and evaluating the results.

Literature Review

As mentioned in the introduction section, there are several factors affecting the price and consumption of natural gas. This study deals with two among those factors: HDD and oil prices. Ever since the work by Hamilton (1983), oil has been recognized as playing a key role in macroeconomic (Sadorsky, 1999; Altıntaş and Kassouri, 2018; Kassouri et al., 2020; Adetutu et al., 2020). When the relevant literature about the effects of oil prices on natural gas prices was examined, it was witnessed that different results were obtained by different studies. On the one hand, Bachmeier and Griffin (2006), Panagiotidis and Rutledge (2007), Ramberg and Parsons (2012), Brigida (2014), Nick and Thoenes (2014), Lin and Li (2015), Jadidzadeh and Serletis (2017), Tatlı and Barak (2020) have concluded that there is a correlation between natural gas prices and oil prices. On the other hand, Mohammadi (2009), Batten et al. (2017) and Caporin and Fontini (2017) concluded that there is not any relationship between natural gas prices and oil prices. In addition to these studies that focus on the correlation, there are studies (Méndez-Carbajo, 2011; Wang and Wu, 2012; Geng et al., 2017) investigating the causality between oil prices and natural gas prices in the literature.

Pérez-Lombard et al. (2008) stated that because of the population, the demand for building services (heating, ventilation, and air conditioning) and the time spent inside buildings are going to increase, and the demand for energy will also going to increase in the future. Accordingly, they emphasized that ensuring energy efficiency in the buildings has been and continues to be the main objective of any government's energy policy at regional, national, and international levels. The impact of global warming on the consumption of energy for underfloor heating and cooling depends on the current and future regional climate conditions and the technical characteristics of the buildings, such as the thermal comfort conditions and the quality of thermal insulation of the buildings. Quantitative predictions of the future consumption of energy are naturally dependent on the underlying assumptions and models used to build different future climate scenarios (Christenson et al., 2006). Some studies (Rosenthal et al., 1995; Belzer et al., 1996; Pretlove and Oreszczyn, 1998; Cartalis et al., 2001) concluded that climate change has important implications in terms of demand for energy in buildings. Cartalis et al. (2001) examined the influence of HDD and cooling degree days (CDD) in the Southeastern Mediterranean region. They found that the regions most affected by CDD are Attica, Central Macedonia, the Aegean Islands, and Crete, while a large part of the region would demand less energy for heating in the case of HDD. In another study, Rosenthal et al. (1995) estimated how global warming affects energy expenditures in the US. They found that a 1°C increase in overall global temperature would reduce the projected energy expenditure of the US.

One of the studies on the relationship between natural gas and climate Chai et al. (2018) argued that Chinese natural gas prices are expensive when compared to global natural gas prices, while economic activities demand, supply and price of alternative fuel are the most important determinants of natural gas prices. They also highlighted that the price elasticity of demand for natural gas is low in China. Harold et al. (2015) examined the determinants of the demand for residential natural gas in Ireland. They emphasized that climatic conditions (HDD, sundials, average cloud cover, daily precipitation, and wind speed), structural characteristics of the houses, and socioeconomic characteristics of the households are the significant factors that affect the demand for residential natural gas. Consequently, they argued that climatic conditions are the most effective factor in terms of daily residential natural gas consumption. Tihanyi and Szunyog (2012) examined the effect of weather change on natural gas consumption based on the statistical analysis of annual and monthly atmospheric temperature levels in European countries for the period 1980-2009. By performing a weather risk assessment, they concluded that the weather is a significant factor for a country in terms of effective and sustainable energy management. Dergiades et al. (2018) stated that weather conditions play an indirect causal role in shaping natural gas spot prices. Timmer and Lamb (2007) found a very high correlation between natural gas consumption and temperature in their study conducted in the Central and Eastern United States. They suggested that more accurate seasonal weather forecasts increase the predictability of natural gas consumption. In their study dealing with the Istanbul (Turkey) case, Goncu et al. (2013) concluded that the HDD is the main determinant of the demand for natural gas. Hu et al. (2014) stated that significant temperature shocks affect both the conditional averages and the variability of natural gas prices. In his study, which was conducted in Alberta, Canada, for the period 1962-1980, Sanderson (1983) reported that the HDD (below 18°C) were strongly correlated with the residential per household consumption of natural gas. Studies dealing with the relationship between natural gas prices and climate are summarized in Table 1.

Tab. 1. Empirical Studies on the Relationship between Natural Gas Prices and Climate

Authors	Country	Year	Method	Result
Hartley and Medlock III (2014)	United States	January 1995-December 2011	ECM, Johansen tests	Natural gas prices are affected by weather conditions and other seasonal factors.
Nick and Thoenes (2014)	Germany	January 2008-June 2012	Structural VAR model	Temperature and supply shocks affect natural gas prices.
Ji et al., (2018)	United States	1999-2017	DAG, VAR/ECM, Variance decomposition	Both changes in natural gas level in storage and seasonality follow a simultaneous and cross-lagged causality with natural gas.
Brown and Yücel (2008)	United States	June 1997-June 2017	ECM	Weather conditions, hurricanes and other seasonal factors have a significant impact on the adjustment of natural gas prices.
Mu (2007)	United States	January 1997-December 2000	GARCH	The weather has a significant impact on natural gas prices.
Gunnarshaug and Ellerman (1998)	United States	1994-1997	OLS	Natural gas prices are influenced mainly by the local heating degrees days.

Note: DAG (directed acyclic graph), VAR (vector autoregression), ECM (error correction model); GARCH (generalized autoregressive conditional heteroskedastic).

When the literature on energy demand and climate relationship is examined, Considine (2000) examined the effects of weather changes on demand for energy. He suggested that a significant portion of the total energy consumption is sensitive to short-run fluctuations in the climate or weather conditions. Ranson et al. (2014) analyzed the effects of climate change on demand for energy for heating the space both in residential and commercial buildings. According to their results, the energy use for heating has been the highest at very low temperatures, while the energy use for cooling has been the highest at very high temperatures. In other words, they concluded that there is a U-shaped relationship between heat and demand for energy. The studies dealing with the relationship between the demand for energy and climate are summarized in Table 2.

Tab. 2. Empirical Studies on the Relationship between Demand for Energy and Climate

Authors	Country	Year	Method	Result
Tol et al. (2012)	157 countries	1970-2002	LSDVC	The temperature elasticity of energy is affected by the temperature level.
Cian et al. (2007)	31 countries	1978-2000	OLS	Demand for natural gas is affected by seasonal effects.
Yi-Ling et al. (2014)	Shanghai	2003-2007	Correlation analysis	The level of energy consumption is higher in the winter and summer months.
Lee and Chiu (2011)	24 OECD countries	1978–2004	PSTR	There is a U-shaped relationship between electricity consumption and temperature.
Altinay and Yalta (2016)	Istanbul (Turkey)	2004-2002	Rolling window framework	The demand for natural gas is sensitive to economic conditions and weather fluctuations.
Gautam and Paudel (2018)	Northeastern United States	1997-2016	DFE, MG, PMG, CCEMG, and AMG	The heating degree days (HDD) have significant positive effects on the demand for natural gas.

Note: OLS (ordinary least squares), PSTR (panel smooth transition regression), LSDVC (least squares dummy variable), DFE (dynamic fixed effects), MG (mean group), PMG (pooled mean group), CCEMG (common correlated effect mean group), AMG (augmented mean group).

Material and Method

a) Data Set

In this study, the effects of climate and oil prices on residential natural gas prices are examined using data from 11 OECD member countries from 1992-2016. In the study, GDP (an indicator of economic growth) is included in the model as a control variable. The countries included in the study are presented in Table 3. The reason behind the fact that all OECD countries are not included in the study and analysis is that some OECD countries have not published any data on natural gas prices in some years. In other words, the remaining OECD countries were excluded from the study due to the missing data.

Tab. 3. List of Countries Examined in the Study

No	Countries	No	Countries
1	Austria	**7**	Spain
2	Canada	**8**	Switzerland
3	France	**9**	Turkey
4	Ireland	**10**	United Kingdom
5	Netherlands	**11**	United States
6	New Zealand		

Consequently, the total data set is composed of 275 data using annual data for 25 years (1992-2016) for each of 11 countries. As Figure 1 shows, both natural gas production and consumption have increased over the years in these countries.

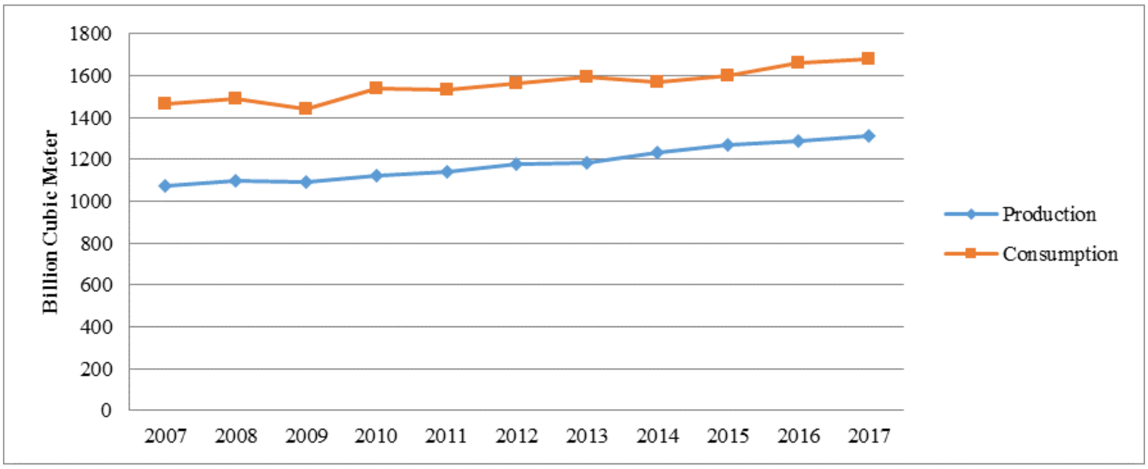

Fig. 1. Natural Gas Production and Consumption in OECD Countries
Source: British Petrol Statistical Review of World Energy.

The explanations for the variables and the sources from which the variables are obtained are given in Table 4. The relationship between the variables used in the study is established in a logarithmic form and presented in equation 1.

$$\ln GP_{it} = \alpha_0 + \alpha_1 \ln OP_{it} + \alpha_2 \ln HDD_{it} + \alpha_3 GDP_{it} + u_{it} \quad (1)$$

Here, $\ln GP$, $\ln OP$, $\ln HDD$ and $\ln GDP$ are the real household sector gas price, real crude oil import price, heating degree days index and gross domestic product, respectively. $\ln GP$ is converted to real form by proportioning to the US GDP deflator.

Tab. 4. Variables and their Descriptions

Variables	Description	Sources
GP	Natural gas prices for household (US dollar/MWh)*	IEA
OP	Crude oil import prices (US dollars/barrel)	Organization for Economic Co-operation and Development (OECD)
HDD	Heating degree days	An index used to estimate the amount of natural gas required for the household sector during the cool season**
GDP	Real GDP at constant 2017 national prices	Penn World Table

Note: *deflated using the GDP deflator of the United States. **HDD=(18^0C–K)*D if K is less than or equal to the heating threshold of 18^0C or zero if K is greater than this threshold, where K is the average outdoor temperature over a period of D days (Yu, Zheng and Han, 2014).

The descriptive statistics of the raw and logarithmic values of the variables that are used in the study are presented in Table 5. The Jargue-Bera statistics indicate that the series is not following a normal distribution.

Tab. 5. Descriptive Statistics

	ln *GP*	ln *OP*	ln *HDD*	ln *GDP*	*GP*	*OP*	*HDD*	*GDP*
Mean	3.811	3.634	5.710	13.781	51.783	49.354	322.149	2348604.000
Median	3.741	3.627	5.615	13.802	42.170	37.610	274.777	987318.600
Maximum	4.778	4.768	6.620	16.765	118.870	117.700	750.567	19097498
Minimum	2.634	-2.525	5.002	11.336	13.940	0.080	148.772	83784.660
Std. Dev.	0.528	0.803	0.334	1.267	26.969	33.926	136.152	4166914.000
Skewness	-0.013	-1.499	1.289	0.379	0.698	0.677	2.069	2.835
Kurtosis	2.118	13.667	4.462	2.997	2.257	2.022	6.562	9.772
Jarque-Bera	8.915	1406.99	100.69	6.606	28.697	32.016	341.737	893.9615
Probability	0.011	0.000	0.000	0.036	0.000	0.000	0.000	0.000
Observations	275	275	275	275	275	275	275	275

The correlation between the variables is presented in Table 6. Accordingly, there is a positive correlation between $\ln GP$ and $\ln OP$, while a negative correlation between $\ln GP$ and $\ln HDD$, $\ln GP$ and $\ln GDP$. These results coincide with the economic expectations.

Tab. 6. Correlation Matrix

	ln *GP*	ln *OP*	ln *HDD*	ln *GDP*
ln *GP*	1			
ln *OP*	0.611	1		
ln *HDD*	-0.472	0.025	1	0.252
ln *GDP*	-0.180	0.065	0.252	1

Contour and surface plots are plotted in order to show the relationship between the variables more clearly. The contour plot is presented in Figure 2, and the surface plot is presented in Figure 3. Both graphs show that when the climate index value is high, natural gas prices are low, and when oil prices are high, natural gas prices are also high. In other words, both graphs show that there is a negative correlation between the climate and residential natural gas prices while a positive correlation between oil prices and residential natural gas prices.

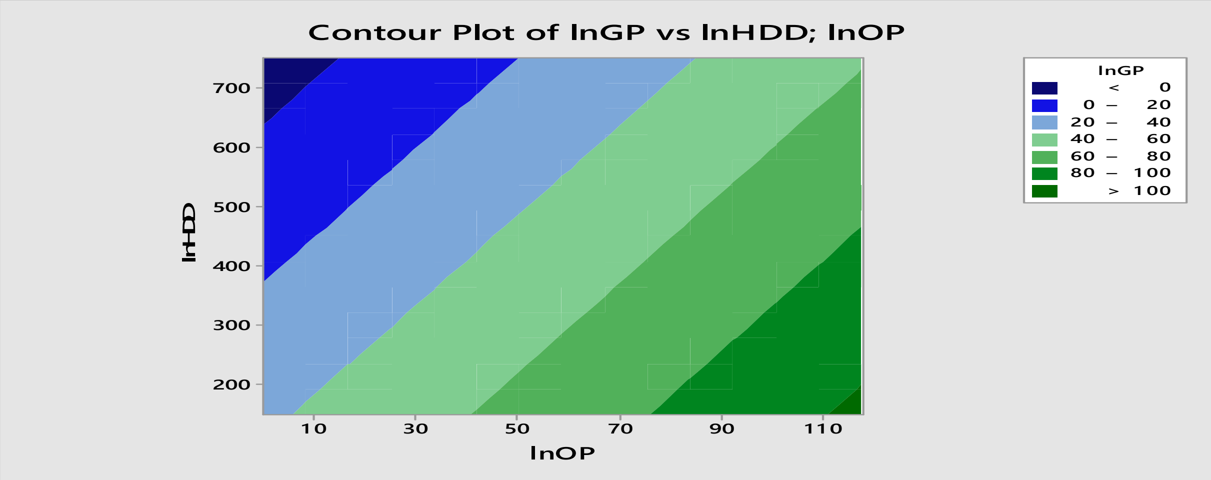

Fig. 2. Contour Plot of lnGP vs lnHDD and lnOP

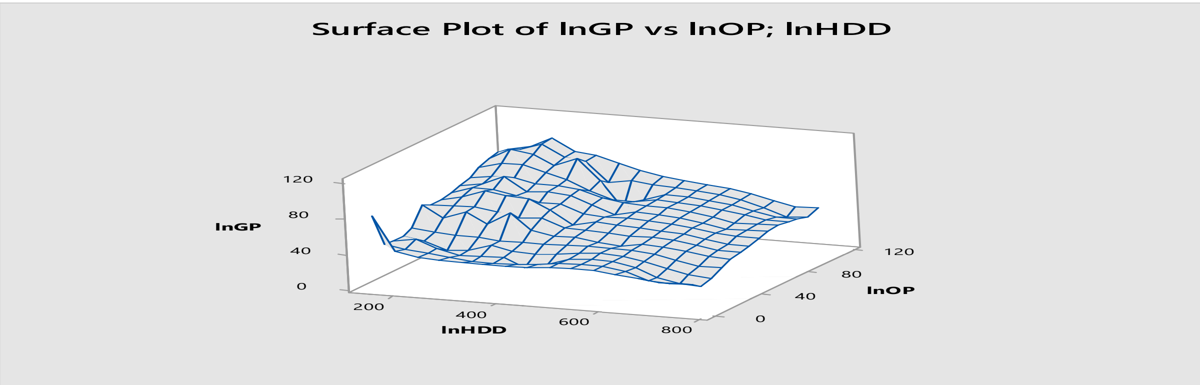

Fig. 3. Surface Plot of lnGP vs lnHDD and lnOP

b) Method

Together with globalization, national economies have become more sensitive to the economic shocks in other countries. For this reason, it is necessary to take into account the possible cross-sectional dependence between countries when conducting panel analysis (Pan et al., 2015). In other words, it is likely that there exists a cross-sectional dependence between economic series. From this viewpoint, the presence of cross-sectional dependence between the series is tested by CD_{LM} (Pesaran, 2004), CD_{LM1} (Breusch & Pagan, 1980), CD_{LM2} (Pesaran, 2004) and $CD_{LM\text{-}Adj}$ (Pesaran et al., 2008) tests.

After testing the cross-sectional dependence between the series, Hadri-Kurozumi, PANIC and CADF (CIPS) unit root tests are applied to determine the stationarity of the series. Hadri-Kurozumi unit root test takes into account both the cross-sectional dependence and the autocorrelation between the series. It also corrects autocorrelation (Göçer, 2013). The null hypothesis of this test is "there is no unit root in the series", while the alternative hypothesis is "there is a unit root in the series".

The null hypothesis of PANIC and CADF (CIPS) unit root tests is "the series is not stationary (i.e. unit root exists)", whereas the alternative hypothesis is "the series is stationary (i.e. unit root does not exist)". The values calculated for the CADF and CIPS unit root test are compared with the table of values calculated by Pesaran (2007). When the calculated CADF statistic is less than the critical value in the table, H_0 is rejected. It means that the data of a given country do not include the unit root. When the calculated CIPS value is less than the critical value in the table, H_0 is rejected. This result shows that no unit root exists in the relevant panel data, including all countries.

Pesaran (2006) suggested the use of the Common Correlated Effects Mean Group (CCEMG) estimator for estimating the long-run coefficients in cases where the cross-sectional dependence exists, and the series are heterogeneous. On the other hand, in the case of homogenous series with cross-sectional dependence, Pesaran (2006) suggested the use of the Common Correlated Effects Pooled (CCEP) estimator (Polat and Yaşar, 2017). In this study, both CCEMG and CCEP estimators are used. These estimators are two of the CCE model tests developed by Peseran (2006) and take into account the cross-sectional dependence. They are based on the least squares method and can be used to estimate both stationary and non-stationary series. Based on this method, it is necessary to examine the cross-sectional dependence, autocorrelation and heteroscedasticity. It is also allowed for slope heterogeneity in the CCEMG model. So, whether this method will be used or not is decided by pre-testing the heterogeneity. In this context, the Delta test, which was proposed by Pesaran and Yamagata (2008), is used to determine whether the series of variables are homogeneous.

The CCE estimator follows a consistent and asymptotic normal distribution when the number of observations (N) and time (T) is infinite (Pesaran, 2006). That is to say that the CCE estimator follows a consistent and asymptotic normal distribution, regardless of the fact that whether the time dimension is more or less than the cross-sectional dimension. In addition, it paves the way for calculating the long-run equilibrium coefficients for each cross-sectional unit. By taking this method into account, the linear panel data model presented in equation (2) was created. In the CCE method, the multifactor error structure in equation (2) was tested for estimating the coefficients.

$$y_{it} = \alpha_i^{'} v_t + \beta_i^{'} x_{it} + \varepsilon_{it} \quad i = 1,2,3........N \quad t = 1,2,3........T \tag{2}$$

In equation (2) v_t is the $n\times 1$ dimensional vector of the observable common correlated effects (fixed, trended or seasonal dummy variables like v_{1t}, v_{2t}, v_{3t},……… v_{1n}). x_{it} is the $k\times 1$ dimensional vector of the observed individual-specific explanatory variables.

$$\varepsilon_{it} = \delta_i^{'} f_t + \omega_{it} \tag{3}$$

In equation (3) the f_t is $m\times 1$ dimensional vector of unobservable common correlated effects, ω_{it} is the individual-specific error (Pesaran, 2006; Pesaran and Tosetti, 2011).

The CCEMG estimator is used to estimate the long-run cointegration coefficients by taking the arithmetic mean of the coefficients for each cross-section. It calculates the long-run cointegration coefficients for each horizontal section, as shown in equation (4). The equation (4) gives the CCE estimate for the individual-specific slope coefficient of each cross-section.

$$\hat{b}_{CCEMG} = N^{-1} \sum_{=1}^{N} \hat{b}_i \tag{4}$$

In equation 4, $\hat{b}_i$ gives the CCE estimate for the individual slope coefficient of each cross-section.

In the case that the slope coefficients (β_i) are the same for each horizontal section unit (β_i=β), the CCEP estimator produces more effective results due to the pooling of the common observable effects on the cross-sections. CCEP, the pooled estimator of β, is defined as given in equation (5) (Pesaran, 2006; Pesaran and Tosetti, 2011).

$$\hat{b}_P = \left(\sum_{=1}^{N} \phi X_i^{'} \overline{M} \mathrm{W} \; X_i \right)^{-1} \sum_{=1}^{N} \phi X_i^{'} \overline{M} W X_i \tag{5}$$

In this study, the CCEP estimator, which allows for the differentiation of the relevant coefficient between countries, is used. In addition, Emirmahmutoglu and Kose (2011) causality test is applied to determine the causal relationship between the variables. Emirmahmutoglu and Kose (2011) consider the level VAR model with $k_i + d\max_i$ lags in heterogeneous mixed panels:

$$x_{i,t} = \mu_i^x + \sum_{j-1}^{k_i + d\max_i} A_{11,ij} x_{i,t-j} + \sum_{j-1}^{k_i + d\max_i} A_{12,ij} y_{i,t-j} + u_{i,t}^x \tag{6}$$

$$y_{i,t} = \mu_i^y + \sum_{j-1}^{k_i + d\max_i} A_{21,ij} x_{i,t-j} + \sum_{j-1}^{k_i + d\max_i} A_{22,ij} y_{i,t-j} + u_{i,t}^y \tag{7}$$

where $d\max_i$ is maximal order of integration suspected to occur in the system for each i. while Equation (6) testing causality from x to y, equation (7) testing causality from y to x. Emirmahmutoğlu and Kose (2011) causality test is a test that can be used when the series is not stationary from the same level, that is when some of the series are I (0), and some are I (1), and cointegration relationship cannot be determined between the variables (Emirmahmutoğlu ve Kose, 2011).

c) Analysis and Findings

There are two types of tests used to examine the existence of the unit root in the series: The first type of tests that do not take account of the cross-sectional dependence are called first-generation unit root tests, while the second type of tests that take account of the cross-sectional dependence are called second-generation unit root tests. That is to say that while some estimators are based on the assumption that the model includes a cross-sectional dependence, some estimators are used under the assumption that the model does not include cross-sectional dependence. In light of these facts, it is necessary to identify whether there is a cross-sectional dependence in the model in order to determine and use the correct estimator. The results of the CD_{LM} (Pesaran, 2004), CD_{LM1} (Breusch and Pagan, 1980), CD_{LM2} (Pesaran, 2004), and $CD_{LM\text{-}Adj}$ (Pesaran et al., 2008) tests were used to test whether there is a cross-sectional dependence in series and models are presented in Table 7.

Tab. 7. Cross-Section Dependence in Series

		$\ln GP$	$\ln OP$	$\ln HDD$	$\ln GDP$
CD_{LM1}	Constant	260.354* (0.000)	158.589* (0.000)	161.822* (0.000)	412.029* (0.000)
	Constant and Trend	273.122* (0.000)	180.173* (0.000)	148.225* (0.000)	411.118* (0.000)
CD_{LM2}	Constant	19.580* (0.000)	9.877* (0.000)	10.185* (0.000)	34.041* (0.000)
	Constant and Trend	20.797* (0.000)	11.935* (0.000)	8.889* (0.000)	33.955* (0.000)
CD_{LM}	Constant	-2.890* (0.002)	-0.598 (0.275)	-2.990* (0.001)	-0.828 (0.204)
	Constant and Trend	-2.905* (0.002)	-0.680 (0.248)	-2779* (0.003)	-1.118 (0.132)
$CD_{LM\text{-}adj}$	Constant	19.262* (0.000)	23.007* (0.000)	4.574* (0.000)	56.679* (0.000)
	Constant and Trend	12.837* (0.000)	23.417* (0.000)	1.040 (0.149)	4.584* (0.000)

Note: *, Illustrates 1% statistical significance. The values in parentheses are P values.

The results revealed that there is a cross-sectional dependence in all constant, and constant and trend models of the series, at a 1% significance level. Therefore, Hadri-Kurozumi (2012), PANIC and CADF-CIPS tests, which are the second-generation unit root tests, are applied for testing the unit root in the series. The results obtained from these three tests are presented in Table 8.

Tab. 8. Panel Unit Root Tests Result

		$\ln GP$	$\ln OP$	$\ln HDD$	$\ln GDP$
Hadri- Kurozumi	Level	19.558* (0.000)	5.853* (0.000)	6.7046* (0.000)	1.570*** (0.058)
	First Difference	-	-	-	-
PANIC	Level	6.968* (0.000)	5.091* (0.000)	7.226* (0.000)	6.555* (0.000)
	First Difference	-	-	-	-
CADF-CIPS	Level	-3.440*	-2.804*	-4.138*	-3.197*
	First Difference	-	-	-	-
CADF Critical Values	%1: -2,23 %5: -2,11 %10: -2,03				

Note: *,**,*** Illustrates 1%, 5%,10% statistical significance, respectively. The maximum number of factors assumed to be 2 in the PANIC test. The values in parentheses are P values.

According to the results of unit root tests, all variables are stationary at a level, and they do not contain a unit root.

As mentioned in the previous section, it is necessary to test the cross-sectional dependence and also homogeneity/heterogeneity of the models for choosing the best method to estimate the relationship between the dependent variable and the independent variables. Accordingly, *Delta Tilde* and *Delta Tilde*$_{adj}$ tests are performed for the examination of homogeneity/heterogeneity, while CD_{LM1}, CD_{LM2} ve $CD_{LM\text{-}Adj}$ tests are applied for testing cross-sectional dependence. The results obtained from these tests are presented in Table 9.

Tab. 9. Homogeneity and Cross-Section Dependence in Model

	Tests	Statistic	Probability
Cross-section dependence	CD_{LM1}	326.089*	0.000
	CD_{LM}	25.847*	0.000
	CD	15.359*	0.000
	$CD_{LM\text{-}adj}$	26.576*	0.000
Homogeneity	*Delta_tilde:*	0.014	0.494
	Delta_tilde_adj:	0.016	0.494

Note: *, Illustrates 1% statistical significance.

As seen in Table 9, the estimated p-values both in *Delta Tilde* and *Delta Tilde*$_{adj}$ tests were more than 10%. Consequently, it was concluded that the model is homogeneous. The homogeneity of the models indicates that the effects of the independent variables (i.e. oil prices and climate) on the independent variable (i.e. residential gas prices) do not differ from country to country. The CCE test, which takes into account the cross-sectional dependence and homogeneity of the model, is used for estimating the long-term coefficients. The results of this test are presented in Table 10.

In general, CCE estimators can be used for parameters with cross-sectional dependence. Using the CCEMG estimator for parameters with heterogeneous slopes and using the CCEP estimator for parameters with homogeneous slopes makes the results more consistent (Kaplan and Aktaş, 2016). Since the models used in the study are found to be homogeneous, it is more accurate to interpret the results obtained using the CCEP estimator. On the one hand, the long-run coefficient of the whole panel data is calculated by the CCEP estimator, which was developed by Pesaran (2006), under the assumption that the coefficients are homogeneous. On the other hand, considering the heterogeneity, i.e. climate and economic characteristics differ between the countries, the CCEMG estimator was performed by using Equation (1). The results obtained from these estimators are presented in Table 10.

According to these results, HDD affects residential natural gas prices significantly and negatively in the long run, regardless of whether CCEMG or CCEP estimator is used. More precisely, an increase in HDD level decreases the residential natural gas price in the relevant OECD countries. On the other hand, the results revealed that there is no significant relationship between the oil prices and the residential natural gas prices, and there is no significant relationship between growth and residential natural gas prices.

Tab. 10. CCE Estimator Test Results

Variables	CCE Mean Group Estimates		CCE Pooled Estimates	
	Coefficient	t-value	Coefficient	t-value
$\ln OP$	-0.143	-1.488	-0.010	-0.085
$\ln HDD$	-0.294	2.170**	-0.257*	-1.855***
$\ln GDP$	-0.351	-0.385	-0.090	-0.203

Note: *, **, *** illustrates 1%, 5%, %10 statistical significance, respectively.

Finally, we check the country-specific effects of oil prices, climate, and growth on residential natural gas prices by CCE estimator. The results from Table 11 show that oil prices do not significantly affect natural gas prices in most of the OECD countries, excluding Austria and the United Kingdom. Oil prices negatively affect the natural gas prices in Austria and the United Kingdom. HDD negatively affect the natural gas prices in Turkey and the United Kingdom while positively in Austria. Furthermore, growth positively affects natural gas prices in the Netherlands, New Zealand, and Switzerland and negatively affects natural gas prices in Spain and United Kingdom.

Tab. 11. Individual Impacts of Countries Used in the Study

Countries	$\ln OP$		$\ln HDD$		$\ln GDP$	
	Coefficient	t-value	Coefficient	t-value	Coefficient	t-value
Austria	-0.307	-2.560**	0.468	2.590*	0.193	0.213
Canada	-0.419	-1.110	-0.944	-0.991	-2.570	-0.685
France	0.164	0.773	-0.335	-1.024	-2.602	-1.311
Ireland	-0.08	-0.941	-0.337	-1.146	0.214	0.918
Netherlands	0.061	0.455	-0.04	-0.345	1.472	2.810*
New Zealand	-0.676	-0.979	-0.835	-1.524	2.637	2.545**
Spain	-0.021	-1.000	0.075	0.465	-2.204	-11.187*
Switzerland	-0.123	-0.634	0.101	0.221	2.813	6.155*
Turkey	0.158	0.721	-0.737	-2.739*	-0.157	-0.539
United Kingdom	-0.61	-4.326*	-0.621	-2.112**	-6.869	-6.395*
United States	0.273	1.167	-0.036	-0.067	3.209	0.970

Note: *, **, *** illustrates 1%, 5%, %10 statistical significance, respectively.

The panel and country-specific results obtained by performing the Emirmahmutoglu-Kose (2011) causality test showed in Table 12. The panel result illustrated that there is bidirectional causality between gas prices and oil prices, gas prices and growth. Furthermore, the panel result shows that there is causality from HDD to gas prices.

Tab. 12. Emirmahmutoglu and Kose (2011) Causality Test Result

Countries	$\ln GP \rightarrow \ln OP$	$\ln OP \rightarrow \ln GP$	$\ln HDD \rightarrow \ln GP$	$\ln GDP \rightarrow \ln GP$	$\ln GP \rightarrow \ln GDP$
	Wald Statistic	Wald Statistic	Wald Statistic	Wald Statistic	Wald Statistic
Austria	15.381* [3] (0.002)	2.971 [5] (0.704)	26.997* [4] (0.000)	3.997 [1] (0.046)	2.011 [1] (0.156)
Canada	7.275* [1] (0.007)	2.489 [1] (0.115)	20.568* [6] (0.002)	4.516** [1] (0.034)	1.845 [1] (0.174)
France	5.90** [1] (0.015)	6.849* [1] (0.009)	13.72** [6] (0.033)	2.761*** [1] (0.097)	0.837 [1] (0.360)
Ireland	0.672 [1] (0.412)	0.072 [1] (0.789)	4.044 [6] (0.671)	2.075 [1] (0.150)	1.134 [1] (0.287)
Netherlands	9.036* [1] (0.003)	4.081** [1] (0.043)	6.664 [6] (0.353)	1.487 [1] (0.223)	0.873 [1] (0.350)
New Zealand	9.069* [1] (0.003)	0.141 [1] (0.707)	2.908*** [1] (0.088)	1.275 [1] (0.259)	1.319 [1] (0.251)
Spain	7.957** [3] (0.047)	8.948*** [4] (0.062)	5.566 [3] (0.135)	1.513 [1] (0.219)	1.588 [1] (0.208)
Switzerland	4.977 [3] (0.173)	49.668* [3] (0.000)	15.535** [6] (0.016)	1.858 [1] (0.173)	2.106 [1] (0.147)
Turkey	3.263*** [1] (0.071)	2.332 [1] (0.127)	5.889 [4] (0.208)	3.605 [2] (0.165)	7.187 [2] (0.028)
United Kingdom	0.214 [1] (0.644)	1.773 [1] (0.183)	1.804 [6] (0.937)	4.053** [1] (0.044)	0.814 [1] (0.367)
United States	30.872* [3] (0.000)	18.463* [4] (0.001)	7.776 [4] (0.100)	4.935** [1] (0.026)	1.265 [1] (0.261)
Panel	100.462* (0.000)	94.989* (0.000)	68.557* (0.000)	50.817 * (0.000)	35.473* (0.035)

Note: The maximum lag length is 6. *, ** and *** Illustrates 1%, 5% and 10% statistical significance, respectively. Lag refers to the appropriate lag length. Schwarz information criterion was used as the Information criterion. The values in parentheses are P values. The values in brackets are lags.

The country-specific results obtained by performing the Emirmahmutoglu-Kose (2011) causality test showed that there is no causality between natural gas prices and oil prices in Ireland and the United Kingdom. On the other hand, while there is a unidirectional causality running from natural gas prices to oil prices in Austria, Canada, New Zealand and Turkey, there is a unidirectional causality running from oil prices to natural gas prices in Switzerland. In addition, there is bidirectional causality between natural gas prices and oil prices in France, the Netherlands, Spain and the US. Based on pooled results, a two-way causality was found between natural gas prices and oil prices. In terms of HDD, it was estimated that a unidirectional causality ran from HDD to natural gas prices in 5 countries (Austria, Canada, France, New Zealand, and Switzerland). The same result was obtained for also the whole sample. Also, country-specific results revealed that there is unidirectional causality from growth to gas prices in Canada, France and the US. There is unidirectional causality from gas price to grow in Turkey.

Evaluation of the Results and Conclusion

This study aimed to analyze the effect of changes in HDD and oil prices on residential natural gas prices in 11 OECD Countries. For this purpose, two CCE estimators, called CCEP and CCEMG methods, were used to estimate the parameters. It was concluded in both methods that the changes in HDD affected residential natural gas prices significantly and negatively. On the other hand, the effect of changes in oil prices on residential natural gas prices in Turkey was found statistically insignificant. According to the results obtained from Emirmahmutoglu-Kose (2011) causality test, there is a unidirectional causality running from HDD to residential natural gas prices. A bidirectional causality was also found between oil prices and residential natural gas prices. According to our study, changes in climate (HDD) affect residential natural gas prices significantly. This result is also supported by the results obtained in the studies of Gunnarshaug and Ellerman (1998), Timmer and Lamb (2007), Goncu et al. (2013), Hartley and Medlock III (2014), Nick and Thoenes (2014), Harold et al. (2015). In addition, our study concluded that there is no correlation between oil prices and residential natural gas prices. This result is supported by the studies of Batten et al. (2017), Caporin and Fontini (2017) and Mohammadi (2009). On the other hand, Geng et al. (2017) obtained a two-way causality between natural gas prices and oil prices. This result supports our finding that there is a two-way causality between natural gas and oil prices.

As natural gas consumption continues to increase, it will continue to replace other types of energy (coal, fossil fuels). The imbalances in the amount of natural gas production and consumption will lead to an increase and imbalance in natural gas prices. Since climatic changes are one of the most important factors affecting residential natural gas consumption, changes in supply and demand will affect natural gas prices. Unexpected and unforeseen climate changes affect residential consumption on the one hand and state policies on the other hand. In energy-dependent countries, policy-makers need to draw a long-run roadmap for minimizing the impact of changes in energy prices. Likewise, they must produce appropriate policies to minimize the impact of unexpected and unforeseen climate changes on households.

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