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Research paper

The daily price and income elasticity of natural gas demand in Europe

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A B S T R A C T

Data from 15 European countries is analysed to provide novel estimates of daily own-price, cross-price and income elasticities of natural-gas-demand from 2016 to 2020. The results show that: *first*, there is a strong-seasonal component in the October–February period during which residential-demand has a higher share on total demand, and gas price is not a determinant factor for most of the countries. This seasonal profile makes price-based tools more effective modifying end-consumer behaviours from March to August when estimated own-price elasticities present larger values in absolute terms. *Second*, there are estimated positive own-price elasticities from October to February in Bulgaria, Luxemburg, Poland, the UK, and Portugal. The first four countries present natural gas prices below the EU-28 average during the analysed period and it is argued that positive elasticities may reflect a disconnection between the price traded on the organized markets and the real price perceived by end-customers. For Portugal, who is currently carrying out a very aggressive policy to become coal-free by the end of 2021, natural gas and coal are mainly consumed in power sector to provide flexibility and back up renewable generation. The limited alternatives to provide these services may explain why coal and natural gas are found to be complementary. *Finally*, it is found that lockdowns due to covid-19 highly impacted on natural gas demand, confirming for the first time in the literature a "double heating effect". Our results help to find when price-based tools by policymakers will influence more effectively natural-gas-demand following economic and environmental goals.

1. Introduction

Natural gas represented, in 2019, 24% of World's total primary energy demand, a role that is set to be preserved in 2040, as highlighted by IEA (2020a) in its central scenario (Stated Policies Scenario). Despite being a traditional fossil fuel, natural gas will be part of the world´s energy mix for many years to come thanks to its characteristic (efficiency, emissions factor, flexibility, or firmness) that allows both reducing emissions when switching from other fossil fuel and being the perfect back-up for renewable generation. Its contribution goes beyond power sector by minimizing the emissions in hard-to-decarbonize sectors due to either economic reasons or high temperature process requirements. Indeed, the great importance of a well-functioning gas market in Europe is well established in the literature (Fetisov et al., 2021).

The European Union (EU) has established challenging emission reduction targets by 2030 and 2050, forcing full decarbonization of the economy (Nyambuu and Semmler, 2020). Tackling this process will imply conducting a major transformation in the energy system. The gas sector will have to face this new context and adapt the gas grid to make it possible for green gas penetration (e.g., biomethane and hydrogen). Governments will have to implement policy measures going from new green taxes to establishing renewable quotas. These policy measures could affect gas prices having an impact on both industry competitiveness and social welfare.

Understanding demand behaviour is crucial to tailor future measures maximizing the contributions to reaching climate goals while minimizing economy distortions. This paper analyses the effects of price changes on European daily gas demand as well as the other main drivers. The results may be interesting for developing fundamental models and general equilibrium models to anticipate demand responses to supply variation. The main hypotheses to be tested in this paper are:

- H1: Natural gas own-price elasticities present a seasonal component.
- H2: Natural gas own-price elasticities vary based on the country.
- H3: Existence of a "Double Heating Effect".

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Table 1
Literature survey of own-price elasticity of natural gas.

Reference	Location	Period	Frequency	Sectorial breakdown	Main results
Maddala et al. (1997)	49 states, USA	1970–1990	Annual	Residential sector	OPE: −0.27 IE: −0.06
Berkhout et al. (2004)	Netherlands	1996	Annual	Residential sector	OPE: −0.2
Asche et al. (2008)	12 European countries	1978–2002	Annual	Residential sector	S-OPE: −0.24 to 0.02 L-OPE: −1.84 to −1.15 S-IE: 0.03 to 0.33 L-IE: 2.09 to 2.25
Joutz et al. (2009)	USA	1980–2001	Monthly	Residential sector	S-OPE: −0.09 L-OPE: −0.18
Serletis et al. (2010)	USA	1960–2007	Annual	Industry	OPE: −0.5 to −0.14
Yoo et al. (2009)	South Korea	2005	Monthly	Residential sector	OPE: −0.243 to −0.226 IE: 0.335 and 0.496
Andersen et al. (2011)	13 OECD countries	1978–2003	Annual	Industry	S-OPE: −0.15 to −0.06 L-OPE: −0.84 to −0.16
Bernstein and Madlener (2011)	12 OECD countries	1980–2008	Annual	Residential sector	S-OPE: −0.24 L-OPE: −0.51 S-IE: 0.45 L-IE: 0.94
Serletis et al. (2011)	15 countries (both non-OECD and OECD)	1980–2006	Annual	Country level	S-OPE: −0.73 to −0.32 L-OPE: −0.65 to 2.17
Wadud et al. (2011)	Bangladesh	1981–2008	Annual	Country level and sectorial breakdown	OPE: −0.25 to 0.15 IE: 0.28 to 0.76
Alberini et al. (2011)	USA	1999–2007	Annual	Residential sector	S-OPE: −0.566 L-OPE: −0.693
Payne et al. (2011)	Illinois	1970–2007	Annual	Residential sector	S-OPE: −0.185
Steinbuks (2012)	UK	1990–2007	Annual	Industry	S-OPE: −0.20 L-OPE: −0.28
Bilgili (2014)	8 OECD countries	1979–2006	Annual	Country level	OPE: 0.90 to 3.76
Dilaver et al. (2014)	OECD Europe	1978–2011	Annual	Country level	L-OPE: −0.16 L-IE: 1.19
Yu et al. (2014)	China	2006–2009	Annual	Residential sector	OPE: −0.779 IE: 1.235
Burke and Yang (2016)	44 countries	1978–2011	Annual	Country level	S-OPE: -0.68 to −0.5 S-IE: 0.7 to 1.13
Sun and Ouyang (2016)	China	2013	Monthly	Residential sector	OPE: −1.431 IE: 0.207
Zhang et al. (2018)	China	1992–2011	Annual	Residential, services, industry, power sector and transportation	S-OPE: −1.00 to 3.10 L-OPE: −0.22 to 5.73 IE: 2.05 to 2.31
Filippini and Kumar (2020)	Switzerland	2010–2014	Annual	Residential sector	OPE: −0.73
Malzi et al. (2020)	29 OECD countries	1980–2016	Annual	Residential sector	S-OPE: −0.0002 L-OPE: −0.0015
Alberini et al. (2020)	Ukraine	2013–2017	Monthly	Residential sector	OPE: 0.16
Joshi (2021)	USA, State level	2001–2015	Monthly	Residential, commercial, industry, and power sector	S-OPE: −1.5 to 0.5

Note: OPE: Own-price elasticity, IE: Income elasticity, S: Short-run; L: Long-run.

2. Literature review

Many recent papers have focused on elasticities relating to the natural gas demand. For example, Dong et al. (2019, Table 1) presented a literature review of previous studies on price and income elasticities of natural gas demand published between 2007 and 2017. Also, Huntington et al. (2019) presented a literature review of various estimates for energy demand responses focusing specially upon lower-income industrializing economies and covering different products including natural gas.

As stated in Huntington et al. (2019), some of the estimated elasticities for natural gas must be assessed carefully, since infrastructure access may explain the different country situations. Moreover, North America and Europe are the largest current integrated markets, thanks to the access to a high level of infrastructure concentration. Despite of these difficulties, knowledge of estimates of own-price, cross-price and income elasticities of natural gas demand has already been shown to be very useful for policy purposes (e.g. Huntington et al. (2019), Labandeira et al. (2017), or Alberini et al. (2020)), and it is particularly important to obtain meaningful estimated elasticities. Table 1 summarizes the main findings of a selection of the most recent literature on the topic.

As Table 1 reflects, literature presents a massive range of estimates of natural gas demand heavily impacted by the period, region or country, timeframe, the use of natural gas and frequency used in the analysis. Focusing exclusively on the studies related to European countries,[1] Berkhout et al. (2004) report price elasticities of demand for natural gas of –0.2 for the Netherlands.

1 A review of recent literature focusing on other countries and regions can be found on the Appendix.

Asche et al. (2008) showed that for 12 European countries (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland, and the UK) and with yearly data from 1978–2002, the estimated short-run own price elasticity for natural gas was from −0.24 to 0.02 while the long-run own-price elasticity was ranging from −1.15 to 1.84. The short-run and long run income elasticity was estimated from 0.03 to 0.33 and from 2.09 to 2.25, respectively. Andersen et al. (2011) analysed 13 countries of the Organization for Economic Cooperation and Development (OECD) from 1978 to 2003 obtaining own-price elasticities ranging from −0.06 to −0.15 (short run) and from −0.16 to −0.89 (long run). Bernstein and Madlener (2011) analysed 12 OECD countries from 1980 to 2008 obtaining estimated own-price elasticities of −0.24 (short-run) and −0.51 (long-run) and income elasticities of 0.45 (short-run) and 0.94 (long-run). Serletis et al. (2011) focused on 15 OECD and non-OECD countries from 1980 to 2006 finding an estimated short-run own-price elasticity for natural gas from −0.32 to 0.73 while the long-run own price elasticity was ranging from −0.65 to 2.17. Steinbuks (2012) studied the case of UK from 1990 to 2007 obtaining an estimated own-price elasticity of −0.20 (short-run) and −0.28 (long-run). Bilgili (2014) considered 8 OECD countries from 1979 to 2006 obtaining own-price elasticities ranging from 0.90 to 3.76. Dilaver et al. (2014) analysed several European countries from 1978 to 2011 finding an estimated own-price elasticity of −0.16 and an estimated income elasticity of 1.19. Burke and Yang (2016) analysed 44 countries over the period 1978–2011 and they find that own-price elasticity varies from −0.50 to −0.68 while income elasticity from 0.70 to 1.13. They also find that long-run price elasticity of natural gas demand point estimates are around −1.25 and an estimated long-run income elasticity of natural gas demand estimates are +1 and above. Labandeira et al. (2017) used a meta-analysis to identify the main factors affecting short and long-term elasticity results for energy, in general, as well as for specific products such as natural gas. They show that for European countries, elasticities usually are negative for own-price elasticities for natural gas. Malzi et al. (2020), using data of 19 OECD countries from 1980 to 2016, find that the income elasticity is positive while price elasticity is negative towards natural gas use in the long run. More recently, Filippini and Kumar (2020) used household-level panel data from 2010 to 2014 for 958 Swiss households showing an estimated own price elasticity of gas demand around -0.73. An inelastic demand is expected as the Swiss gas demand originates mainly from space heating and water heating purposes.

However, all the previous literature relates to using yearly/ quarterly and/or monthly datasets. The value of obtaining daily elasticities is well established outside of the energy demand literature (even though using daily data increases the noise versus using for example yearly or monthly data) with plenty of examples in finance[2] and economics.[3] Despite the importance, empirical estimates of high-frequency (e.g., hourly, or daily) elasticities are hardly available in the energy literature due to the lack of daily data available, with the exception of power markets in which market design, renewable energy sources development and hourly dispatching mechanism have contributed to generate the data necessary to this kind of analysis (e.g. Lijesen (2007); Vesterberg (2016); or Andruszkiewicz et al. (2020)).

There are three main reasons for the need of high-frequency estimated elasticities: (1) Data disaggregation produces lower (in absolute value) price elasticities, as already shown in the literature (e.g. Bohi (1981); McClung (1988); Espey and Espey (2004); or Dagher (2012)) from the empirical point view. Indeed, Kim (2004) found that electricity and natural gas demand are more price inelastic in combined-billed markets. Also, Vesterberg (2016) found differences between daily and hourly estimated elasticities of electricity. (2) Dagher (2012) also shows that when dealing with natural gas, the higher volatility tends to happen in the short run, motivating changes in the usage of existing equipment, instead of in the long run (when changes in the equipment stock are produced). Possible explanations are that consumers may have already modified their infrastructure to previous price shocks; and/or, most of price changes are less than 1% from month to month. Such small monthly changes may not be perceived by the consumer; or even if they are perceived, there is not a large incentive to introduce changes in the use or the equipment stock. On the contrary, bigger price changes (that can happen for example at daily frequency) are expected to motivate and induce changes in the use of the equipment if the alternative infrastructure is already in place, as highlighted by Westley (1992). It is important to highlight that this is not contrary to the fact that the potential effect in the long run might be higher, especially if it implies investment on infrastructure ready for alternative fuels. And (3), Dagher (2012) also shows that the use of high-frequency elasticities allows to provide a more detailed explanation of the price adjustment through the time path that can be very useful for policy makers. All this justifies the need to obtain high frequency estimates of elasticities. This paper tries to fill this gap in the energy literature by providing novel estimated daily elasticities for natural gas demand obtained from analysing daily consumption data of 15 European countries. The daily frequency of this dataset allows the model to estimate dynamic elasticities at a daily level and also to estimate long-run elasticities uncovering the daily dynamics of the natural gas demand. We analyse an extended daily period from 2016 to 2020 that allows us also to study the effects of the lockdowns due to the Covid-19 in the natural gas demand.

3. Model

Following Zhang et al. (2018),[4] we construct an autoregressive distributed lag (ARDL) model and, following Labandeira et al. (2012) – where they allowed for province and/or time specific elasticities-, we also introduce iteration effects to allow for possible elasticities that may be country and/or time varying. The model has the following shape with a double logarithmic specification in a panel data context (Wooldridge (2010); and Tovar and Iglesias (2013)):

$$lnQ^{g}_{i,t} = \alpha_0 + \sum_{j_1=1}^{u_1} \alpha_{1,j_1} lnQ^{g}_{i,t-j_1} + \sum_{j_2=0}^{u_2} \alpha_{2,j_2} lnP^{g}_{i,t-j_2} + \sum_{j_3=0}^{u_3} \alpha_{3,j_3} lnIPI_{i,t-j_3} + \sum_{j_4=1}^{11} \alpha_{4,j_4} dumon_{j_4} * lnP^{g}_{i,t}$$

2 E.g. Aouadi et al. (2018) obtained daily elasticities of stock market liquidity to information demand and Cao et al. (2021) estimated daily stock market index´s elasticities.

3 E.g. Mladenovic and Petrovic (2010) estimated daily semi-elasticities of money demand; Fornari et al. (2002) estimated daily elasticities between news on the exchange rate of lira and price changes, and Thakral and Tô (2021) focused on elasticity of labour supply with respect to average daily wages.

4 As stated in Zhang et al. (2018, page 336), there is clear evidence in the literature that the ARDL model yields consistent estimates regardless if the regressors are I(1) or I(0); and that also, the ARDL model is the general form of the error correction model and the partial adjustment model, where these two specifications impose unreasonable constraints on short and long run elasticities. The double logarithmic form used in (1) at price level has been commonly used in the literature e.g. Alberini et al. (2020), Labandeira et al. (2012); Steinbuks (2012); Zhang et al. (2018); Filippini and Kumar (2020); or Burns (2021).

$$
\begin{aligned}
&+\sum_{j_5=1}^{14}\alpha_{5,j_5} ducountry_{j_5} * lnP^{g}_{i,t}\\
&+\sum_{j_5=1}^{14}\alpha_{6,j_5} ducountry_{j_5} * lnP^{c}_{i,t}\\
&+\sum_{j_5=1}^{14}\alpha_{7,j_5} ducountry_{j_5} * lnP^{CO_2}_{i,t} + \sum_{j_6=0}^{u_4}\pi_{1,j_6} HDD_{i,t-j_6}\\
&+\sum_{j_7=0}^{u_5}\pi_{2,j_7} HDD^2_{i,t-j_7}\\
&+\sum_{j_8=0}^{u_6}\pi_{3,j_8} CDD_{i,t-j_8} + \sum_{j_9=0}^{u_7}\pi_{4,}j_9 CDD^2_{i,t-j_9}\\
&+\sum_{j_{10}=0}^{u_8}\pi_{5,j_{10}} \text{LOCK\_DOWN}_{i,t-j_{10}}\\
&+\sum_{j_{11}=0}^{u_9}\pi_{6,j_{11}} \text{LOCK\_DOWNxPeak}_{i,t-j_{11}} + \mu_i + \varepsilon_{i,t} \qquad (1)
\end{aligned}
$$

where $i = 1,\ldots,N$ indicates the country and $t = 1, \ldots, T$ the time period. For country i and time period t, $Q^g_{i,t}$ denotes the demand for natural gas[5]; $P^g_{i,t}$ is the real price of natural gas; $IPI_{i,t}$ is the real Industrial Price Index; $P^c_{i,t}$ is the real price of coal as an alternative energy; $P^{CO_2}_{i,t}$ is the real price of CO_2 emissions; μ_i is the unobservable country fixed effects and $\varepsilon_{i,t}$ the unobservable idiosyncratic error term. Dummies for year, day (they were not statistically significant), month (*dumon*) and country (*ducountry*) were also included in (1) in the consideration of possible spatial and temporal effects on the consumption of natural gas and iteration effects as in Labandeira et al. (2012). The year 2017, month December, Day 1 and country Slovenia was taken as the reference to avoid de dummy variable trap. We also included other independent variables in Eq. (1) such as real prices of CO_2 and coal as independent variables, but they were not statistically significant. Finally, variables to capture the effect of the lock-down due to the covid-19 (LOCK_DOWN); an iteration effect of the LOCK_DOWN variable multiplied by a variable capturing the peak-day in each of the countries of natural gas demand (Peak), i.e., LOCK_DOWNxPeak; Heating Degree Days (HDD) and Cold Degree Days (CDD) –including their squares in order to allow for possible existence of non-linear relationships between climate variables and natural gas consumption, as in Labandeira et al. (2012) – more information about these variables is given in the following Section and Appendix.

We allow for the existence in (1) of lags u_1, u_2,…, u_9 and following Zhang et al. (2018), we select them according to F-tests and t-tests to check the statistical significance of the variables as model selection criteria and the within-R^2. From (1), we obtain the following daily short and long-run elasticities of natural gas:

- Short-run own-price elasticity of natural gas demand for country j_5 in a day of month j_4 as[6]

$\alpha_{2,0} + \alpha_{4,j_4} + \alpha_{5,j_5}$

- Long-run own-price elasticity of natural gas demand for country j_5 in a day of month j_4 as[7]

$$(\sum_{j_2=0}^{u_2}\alpha_{2,j_2} + \alpha_{4,j_4} + \alpha_{5,j_5})/(1 - \sum_{j_1=1}^{u_1}\alpha_{1,j_1})$$

- Short-run cross-price elasticity of natural gas demand for country j_5 with regard to coal as[8]

α_{6,j_5}

- Long-run cross-price elasticity of natural gas demand for country j_5 with regard to coal as[9]

$$\alpha_{6,j_5}/(1 - \sum_{j_1=1}^{u_1}\alpha_{1,j_1})$$

- Short-run cross-price elasticity of natural gas demand for country i with regard to CO_2 emissions[10]

α_{7,j_5}

- Long-run cross-price elasticity of natural gas demand for country j_5 with regard to CO_2 emissions[11]

$$\alpha_{7,j_5}/(1 - \sum_{j_1=1}^{u_1}\alpha_{1,j_1})$$

- Short-run income elasticity of natural gas demand for any country is

$\alpha_{3,0}$.

- Long-run income elasticity of natural gas demand for country i with regard to CO_2 emissions is

$$\sum_{j_3=0}^{u_3}\alpha_{3,j_3}/(1 - \sum_{j_1=1}^{u_1}\alpha_{1,j_1}).$$

We can also obtain from (1) the short and long run impact of the "double heating effect" due to the lockdown — see Section 4 for more details as follows

- Short-run effect in any day (it does not include the cumulative effect of the peak day of demand of natural gas and the lockdown) is $\pi_{5,0}$.
- Long-run effect in any day (it does not include the cumulative effect of the peak day of demand of natural gas and the lockdown) is $\sum_{j_{10}=0}^{u_8}\pi_{5,j_{10}}/(1 - \sum_{j_1=1}^{u_1}\alpha_{1,j_1})$.

5 One crucial difference is the infrastructure available in the countries to use (to demand) natural gas and it may affect domestic, industrial, and commercial demand; and may often dictate different responses within and between countries beyond the use of for example fixed effects. In our empirical application, we use an aggregation of natural gas without differencing the structure of consumption by sector or by the purpose of demand (natural gas could be also used to produce electricity by energy firms, for instance). We would have liked to have used data disaggregated by sectors, but unfortunately such data was not available at daily frequency for the 15 countries in our sample.

6 If the country and the month are the ones that are taken as the reference in order to avoid the dummy-variable trap then it will be only $\alpha_{2,0}$.

7 If the country and the month are the ones that are taken as the reference in order to avoid the dummy-variable trap then it will be only $(\sum_{j_2=0}^{u_2}\alpha_{2,j_2})/(1-\sum_{j_1=1}^{u_1}\alpha_{1,j_1})$.

8 If the country is the one that is taken as the reference in order to avoid the dummy-variable trap then it will be zero.

9 If the country is the one that is taken as the reference in order to avoid the dummy-variable trap then it will be zero.

10 If the country is the ones that is taken as the reference in order to avoid the dummy-variable trap then it will be zero.

11 If the country is the ones that is taken as the reference in order to avoid the dummy-variable trap then it will be zero.

- The short-run effect in any day (including the cumulative effect of the peak day of demand of natural gas and the lockdown) is $\pi_{5,0} + \pi_{6,0}$.
- Long-run effect in any day (including the cumulative effect of the peak day of demand of natural gas and the lockdown) is $(\sum_{j_{10}=0}^{u_8} \pi_{5,j_{10}} + \sum_{j_{11}=0}^{u_9} \pi_{6,j_{11}})/(1 - \sum_{j_1=1}^{u_1} \alpha_{1,j_1})$.

4. Data

This study has been developed using daily data for the period that goes from October 1st, 2016, to November 30th, 2020, from 15 European countries, generating $N = 15$ and $T = 1522$ observations, utilizing all the sample size that was available. Although the initial intention of this study was to model the demand of all the countries in European Union, restrictions on the access to the data led us to limit our analysis to 15 countries.[12] Despite this limitation, the countries sample represents consistently over the period of analysis more than 80% of the EU28 natural gas consumption. Considering these 15 countries (all of them EU members that follows similar market rules and have a quite homogeneous access to gas infrastructure) limits the potential distortion on price–demand interaction due to different natural gas infrastructure build-in levels highlighted by Huntington et al. (2019). The daily natural gas consumption data has been extracted from the daily operational data of the different European Transmission System Operators (TSOs).

The gas prices series were created based on the traded daily closing prices[13] of the spot reference of the different hubs retrieved from Thomson Reuters (2021), harmonized to use the same counting unit (€/MWh).

Labandeira et al. (2012) used several extrapolating-procedures to obtain for example gross disposable income of households by provinces that imply breaking the data into quarters and later inflating it according to the evolution of the Consumer Price Index. Also in Labandeira et al. (2012), several proxies were used in those cases where the real variables were not available. We apply similar extrapolating procedures in our case as well as several proxies that we describe in what follows.[14]

The CO_2 price used is the closing price of the European Union Allowance (EUA) of the EU Emissions Trading System (EU ETS) retrieved from Sendeco2. As a proxy of the coal price in Europe we have use the daily closing price of the CIF ARA, retrieved from Thomson Reuters (2021).

All prices were converted into real terms by using the harmonized index of consumer prices (HICP) published by Eurostat, extrapolating a daily variation from monthly data for each and every country of study (see the Appendix).

The economic activity data correspond to the Production in Industry Index,[15] neither seasonally- nor calendar-adjusted and with base 2015, published by Eurostat. We transformed monthly dataset into a daily data by generating "*bridge*" values through a daily-compounded growth rate that considers exclusively working days.[16]

Regarding climatic variables, we have utilized the variables Heating Degrees Days (HDD) and Cooling Degrees Days (CDD). In order to construct those variables, we started from the IEA; CMCC (2020a) database where the daily average temperature for each country is calculated based on the 2 m above the surface temperature measurements of the different weather stations weighed by population of their area of influence.[17] Using the daily average temperature for each country of study and following Labandeira et al. (2012), HDD and CDD were calculated taking eighteen degrees Celsius as ideal temperature, considering an interval of plus/minus five degrees in which there are no relevant heating or cooling needs. Therefore, these variables have been defined as the degrees of deviation from the temperature comfort interval, identifying this way the energy needs to achieve the comfort temperature.

Additionally, a variable named LOCK_DOWN was included to analyse the impact of the measures established to tackle the covid health crisis. To define this variable, we used a database of the *Oxford Covid-19 Government Response Tracker* project developed by the Blavatnik School of Government to assess the different governments' response to the covid pandemic. Therefore, the LOCK_DOWN variable corresponds with their Stringency Index, reformulated while using their methodology available in Hale et al. (2020), to limit the analyses to the measures designed to minimize social interaction and control the virus spreading.[18] Finally, an iteration effect of the LOCK_DOWN variable multiplied by a variable capturing the peak-day in each of the countries of natural gas demand (Peak) was also included, creating the variable named LOCK_DOWNxPeak (the peak day of the lockdown corresponds to the natural gas demand peak day for each country since the World Health Organization (WHO) declared COVID-19 a pandemic, on March 11th, 2020).

Descriptive statistics of the variables used in the model are provided in Table 2. Unit root testing on all variables was performed using a battery of tests that goes from Levin et al. (2002), Im et al. (2003), and the Hadri (2000) Lagrange multiplier (LM) tests. The Levin et al. (2002) and Im et al. (2003) tests have as the null hypothesis that all the panels contain a unit root. The Hadri (2000) Lagrange multiplier (LM) test has as the null hypothesis that all the panels are stationary. All the variables are proved to be stationary or I(0) no matter the unit root test selected. The Levin et al. (2002) test results are especially relevant to our analysis, since it requires that the number of time periods grow more quickly than the number of panels, so the ratio of panels to time periods tends to zero.

5. Results

5.1. Own-price, cross-price, and income elasticities

In relation to the estimation procedure, in (1) we have a dynamic panel where $N = 15$ and $T = 1522$, our T is much larger than N. Therefore, we should not use the methodology Arellano and Bond (1991) and Bond (2002) that requires a large N. The bias from using fixed effects with lagged dependent variables is small when T is large. Therefore, we proceed to estimate (1) by fixed

12 Austria, Belgium, Bulgaria, Croatia, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Poland, Portugal, Slovenia, Spain, and United Kingdom.

13 Austria (VTP), Belgium (ZEE), France (PEG), Germany (NCG/GPL) Italy (PSV), Netherlands (TTF), Spain (MIBGAS), United Kingdom (NBP).

14 We use previous literature such as Labandeira et al. (2012) as a guidance for the interpolation procedures. Interpolation induces autocorrelation which is an artefact of interpolation methods. This in turn is expected to affect the choice of the lag order of model (1). We consider this issue by allowing for the use of different lag orders in the estimation of model (1).

15 Mining and quarrying; manufacturing; electricity, gas, steam, and air conditioning supply included in sections B, C and D of the Statistical Classification of Economic Activities in the European Community (NACE Rev.2).

16 To have additionally information about the transformation process, see Appendix.

17 For additional information on the methodology followed by the IEA and CMCC, consult (IEA; CMCC (2020a,b)).

18 The Stringency Index has been reformed to evaluate the impact on gas consumption limiting the included categories to Containment and closure measures only. To have additionally information see Appendix.

Table 2
Descriptive statistics.

Variable	Mean	Standard deviation	Minimum	Maximum	Skewness	Kurtosis
QG	810.04110	974.13110	8.28595	5642.54000	1.61626	5.27640
PG	16.77097	6.16705	3.10000	76.00000	0.45626	6.00712
PC	10.60709	2.43133	6.16871	14.80224	−0.16995	1.65048
PCO2	16.83229	8.53685	4.29945	30.41892	−0.24177	1.44408
IPI	105.49440	9.51004	59.00000	136.10000	−0.37008	5.02891
HDD	3.54125	4.51415	0.00000	26.89689	1.22175	3.80525
CDD	0.08862	0.47024	0.00000	6.80201	6.65851	54.24517
LOCK_DOWN_S	9.89383	22.77017	0.00000	95.83333	2.13282	6.11278

effects[19] with Driscoll and Kraay (1998) standard errors, which allow any correlation across countries and general serial correlation across time. Driscoll and Kraay (1998) standard errors are robust to very general forms of cross-sectional (spatial) and temporal dependence when the time dimension becomes large (in our panel T is much larger than N). This nonparametric technique of estimating standard errors does not place any restrictions on the limiting behaviour of the number of panels. The results are provided in Table 3,[20] where we use the notation that when a variable is followed by ".Lu" it means that we have introduced lag "u" of that variable following (1). $Dumon_3$, …., $Dumon_9$ refer to the dummy variables of months from March to September, and Ducountry_x refers to the dummy of country x where we have obtained statistically significant effects in Table 3 for Poland (PL), United Kingdom (UK), Luxembourg (LU), Bulgaria (BG), Portugal (PT), Austria (AT) and Croatia (HR). From Table 3, we see that all variables are statistically significant at least at 10% level except the p-value corresponding to the income elasticity that is very close to 10%. An F-test where the null hypothesis is that all the variables are not statistically significant is rejected with a p-value of 0.00.

Table 3
Estimated results of (1) for natural gas demand. Within-R2 = 0,9781.

Variable	Estimated value	Driscoll/Kraay Std. Err.	P-value
$\ln Q^g$.L3	0.3655530	0.147049	0.042
$\ln P^g$.L7	−0.5929023	0.172250	0.011
lnIPI.L2	0.3781897	0.230937	0.146
HDD.L2	0.0078953	0.004004	0.089
CDD.L1	−0.0296030	0.005539	0.001
HDD^2.L6	0.0005722	0.000060	0.000
CDD^2.L6	0.0047552	0.001567	0.019
LOCK_DOWN.L3	0.0027795	0.000994	0.027
LOCK_DOWNxPeak.L7	0.0008632	0.000236	0.008
$Dumon_3{}^*\ln P^g$	−0.4334454	0.189099	0.056
$Dumon_4{}^*\ln P^g$	−0.7782381	0.280075	0.027
$Dumon_5{}^*\ln P^g$	−1.1829060	0.255380	0.002
$Dumon_6{}^*\ln P^g$	−1.8095000	0.189266	0.000
$Dumon_7{}^*\ln P^g$	−2.2085330	0.318070	0.000
$Dumon_8{}^*\ln P^g$	−2.1594300	0.407365	0.001
$Dumon_9{}^*\ln P^g$	−1.4235200	0.443041	0.015
$Ducountry_{PL}{}^*\ln P^g$	1.2301500	0.131734	0.000
$Ducountry_{UK}{}^*\ln P^g$	0.3392442	0.127993	0.033
$Ducountry_{LU}{}^*\ln P^g$	0.3357466	0.138805	0.046
$Ducountry_{BG}{}^*\ln P^g$	0.6604148	0.108425	0.000
$Ducountry_{PT}{}^*\ln P^g$	0.9182855	0.163101	0.001
$Ducountry_{AT}{}^*\ln P^c$	0.9513752	0.107608	0.000
$Ducountry_{PT}{}^*\ln P^c$	−1.2539740	0.212232	0.001
$Ducountry_{UK}{}^*\ln P^c$	0.5175868	0.209701	0.043
$Ducountry_{AT}{}^*\ln P^{CO_2}$	0.2450632	0.064153	0.007
$Ducountry_{HR}{}^*\ln P^{CO_2}$	0.2419285	0.068997	0.010
constant	0.4218411	0.995541	0.684

In what follows, we will show that indeed natural gas demand has important information at daily basis — see the dynamics at daily basis for the lagged dependent variable that we allow in model (1) and the lags of independent variables that we find that are statistically significant in Table 3, that we can uncover to obtain more precise estimates of elasticities at daily level.

As stated in previous sections and based on our data, we have focused on total demand elasticity in (1), so our results are not perfectly comparable with some of the literature on the topic that provides either sectorial segmentation (such as Labandeira et al. (2012) for electricity or Zhang et al. (2018) for natural gas) or are based on a database with a different frequency. Our estimations from Table 3 show that elasticity in Europe has a strong seasonal profile. From Table 3, we have computed in Table 4 the estimated short-run own price elasticities for all analysed countries of the EU that are different from the five countries where in Table 3 we have estimated proper estimated elasticities (we denote them EU*).

As shown in Table 4, in the period October–February during which residential demand has a higher share on total demand, mainly due to heating demand, gas price is not a determinant factor for all EU* countries. On the contrary, in those months with lower heating demand, we find estimated negative short-run own price elasticity with continuously increasing values in absolute terms starting from March, peaking in July, and reducing in August and September. This is supported by other sectors' behaviour more sensible to price fluctuations such as power sector. If we average the daily elasticities to compute a unique daily constant elasticity for the whole year for the EU* countries that is not varying per month, we obtain an average daily short-run own-price elasticity of natural gas demand of almost −0.60, showing, overall, a lack of response to price fluctuations. Moreover, we find that during the months from May to September (see Table 4), most of the analysed EU countries show elastic own-price elasticities, implying that pricing policies (such as taxation, subsidies, or regulatory tools) will result in a more than proportional reduction in natural gas demand. This knowledge may be very relevant for designing energy policies since the results of those may differ depending on the month of the year, jeopardizing part of their potential environmental benefits.

On a country basis, we observe in Table 4 how five countries (Poland, Portugal, Bulgaria, Luxembourg, and United Kingdom) present a slightly different behaviour with the rest of the EU* countries, with lower elasticity in absolute terms in the summer season – March to September – while preserving the expected signs, and positive values during the winter season.[21] We argue

19 The Hausman test for random versus fixed effects, provides a p-value much smaller than 0.05 providing evidence that we should use the fixed effects estimator. Also intuitively, a model with fixed effects seems to be adequate because the individual sample (countries) is more a population than a sample and the number of countries is very small as regards the number of time periods.

20 The use of instrumental variables is advisable since errors in variables are introduced in model (1) when mixing data with different frequencies. However, using a daily frequency makes that finding instrumental variables is extremely difficult due to the limited number of variables at that frequency that we can use, and this limits our possibilities of applying robustness checks for our results.

21 If we compute unique daily constant elasticities for the whole year for those five countries that are not varying per month, we obtain that three of

Table 4
Estimated short-run own price elasticities.

	Month_1	Month_2	Month_3	Month_4	Month_5	Month_6	Month_7	Month_8	Month_9	Month_10	Month_11	Month_12
EU*	0.000	0.000	−0.433	−0.778	−1.183	−1.810	−2.209	−2.159	−1.424	0.000	0.000	0.000
PL	1.230	1.230	0.797	0.452	0.047	−0.579	−0.978	−0.929	−0.193	1.230	1.230	1.230
PT	0.918	0.918	0.485	0.140	−0.265	−0.891	−1.290	−1.241	−0.505	0.918	0.918	0.918
UK	0.339	0.339	−0.094	−0.439	−0.844	−1.470	−1.869	−1.820	−1.084	0.339	0.339	0.339
LU	0.336	0.336	−0.098	−0.442	−0.847	−1.474	−1.873	−1.824	−1.088	0.336	0.336	0.336
BG	0.660	0.660	0.227	−0.118	−0.522	−1.149	−1.548	−1.499	−0.763	0.660	0.660	0.660

EU* represents the estimated values for all EU countries except PL, PT, UK, LU and BG.

Table 5
Estimated long-run own price elasticities.

	Month_1	Month_2	Month_3	Month_4	Month_5	Month_6	Month_7	Month_8	Month_9	Month_10	Month_11	Month_12
EU*	−0.935	−0.935	−1.618	−2.161	−2.799	−3.787	−4.416	−4.338	−3.178	−0.935	−0.935	−0.935
PL	1.004	1.004	0.321	−0.222	−0.860	−1.848	−2.477	−2.399	−1.239	1.004	1.004	1.004
PT	0.513	0.513	−0.170	−0.714	−1.352	−2.339	−2.968	−2.891	−1.731	0.513	0.513	0.513
UK	−0.400	−0.400	−1.083	−1.626	−2.264	−3.252	−3.881	−3.803	−2.644	−0.400	−0.400	−0.400
LU	−0.405	−0.405	−1.089	−1.632	−2.270	−3.257	−3.886	−3.809	−2.649	−0.405	−0.405	−0.405
BG	0.106	0.106	−0.577	−1.120	−1.758	−2.746	−3.375	−3.297	−2.137	0.106	0.106	0.106

EU* represents the estimated values for all EU countries except PL, PT, UK, LU and BG.

that a possible explanation to the positive values of the estimated elasticities for these five countries could be a disconnection between the price traded on the organized markets and the real price perceived by end-customers. Thus, during the winter season when heating demand increases, end costumers prioritize meeting their needs over any price signal, especially if that price signal is a regulated tariff that does not reflect the market conditions and that could be partially subsidized. As stated in Zhang et al. (2018), market distortions arise when low prices are present, so that price increases are not followed by reductions in gas consumption. According to Eurostat data, four of the five countries with positive estimated elasticities during winter season (Poland, Bulgaria, Luxembourg, and United Kingdom) present natural gas prices for household consumers below the EU-28 average during the whole period of analysis. Portugal's gas prices for household consumers are over the EU-28 average, both including and excluding taxes and duties. In this case, we argue that the Portugal characteristics may be the key factor to explain our result. As stated in Huntington et al. (2019), different infrastructure access in the natural gas market may induce different responses in the countries. Table 3 shows that natural gas and coal behave as complementary goods in Portugal, limiting alternative options to meet the energy needs.

In Table 5 we have computed the estimated long-run own price elasticities for the EU* countries and the five countries with specific estimated long-run price elasticities that we obtained from Table 3. As shown in Table 5, long-run own-price elasticities follow a similar trend than short-run own-price elasticities. During the winter season (October to February), own-price elasticities are negative in general (except for Poland, Portugal, and Bulgaria), close to one and almost double the short-run own-price elasticity values. During the summer season, price elasticities increase in absolute terms, almost doubling the values seeing in the short-run elasticities. The average long-run own-price elasticity of natural gas demand if it would be a constant value for all the year is around −1.87, higher than the results obtained by Bilgili (2014); Dilaver et al. (2014) or Burke and Yang (2016) – where they used lower frequency data than in our case-.

In relation to the estimated long-run income elasticity, Table 3 shows a value of 1.38, totally in line with previous works Burke and Yang (2016) but higher that what Huntington et al. (2019) obtained.

them present negative estimated daily average short-run own price elasticities, with the only exceptions of Poland with 0.39 and Portugal with 0.12.

Table 6
Estimated long-run effects for lockdown and peak days during lockdown.

Long-run effects	Estimated value
LOCK_DOWN	0.0043810
LOCK_DOWNxPeak	0.0057415

Our findings have relevant policy implications regarding price and income measures effectiveness. We show that when policymakers use price-based tools to influence the natural gas demand in Europe, these policies will be more effective during the months from March to August that is when our estimated own-price elasticities present larger values in absolute terms. Moreover, we find that during the months from May to September (see Table 4), most of the analysed EU countries show elastic own-price elasticities, implying that pricing policies will result in a more than proportional reduction in natural gas demand. This knowledge may be very relevant for designing energy policies since the results of those may difference depending on the month of the year. If this fact is not taken into account and tax mechanisms are not applied to all fossil fuels coherently, the higher elasticity of natural gas during the months from May to September can send the wrong signal to the market and contribute to the use of more polluting alternative fuels, such as coal, jeopardizing part of the potential environmental benefits.

5.2. Double-heating effect

Covid-19 has had an impact that has gone further than a health and economic crisis. The Euro Area's GDP fell 7.2% in 2020, with impacts on all economic sectors IMF (2021). The natural gas sector has not been an exemption. 2020 was the largest recorded demand downturn of natural gas in history, as highlighted by IEA (2021). But covid's impact has gone beyond this global fossil gas consumption downfall since lock down measures could have changed normal patterns of natural gas demand.

Residential gas consumption was expected to increase as millions of people in Europe were forced to spend more time at home. Despite teleworking protocols, many offices and working centres must continue opening, commercial use should remain steady, generating a so-called 'double-heating effect' that could lead to potential increase in use of natural gas. Although many sources in the sector pointed to the possibility of the existence of this effect (e.g. Stapczynski and Blas (2020)), we have not found, from the best of our knowledge, any reference in the academic literature corroborating its existence and quantifying its impact on total natural gas demand. Using the results of Table 3, we computed Table 6 with the long-run effects for the lockdown. The results in Tables 3 and 6 show empirically that the double-heating effect does exist, confirming that it has a positive effect on gas consumption. Thus, an increase of one point on the Stringency Index used to define the LOCK_DOWN variable would generate an increase of 0.42% of the daily gas consumption.

Based on the 'double-heating effect' definition we have established; it is likely that this effect has a stronger impact on peak demand rather than on total demand. To test this hypothesis, and thanks to have defined the sample based on daily observations, we introduced a dummy variable that equals 1 on the peak demand day once the World Health Organization (WHO) declared COVID-19 a pandemic, on March 11th, 2020 (named Peak). Our analysis shows the product of this variable and LOCK_DOWN to be statistically significant in Table 3, determining a higher positive impact on natural gas consumption when markets face peak needs. The impact on daily gas consumption would increases until 0.54% as shown in Table 6.

The existence of a 'double-heating effect' may have long-term implications for policymakers if new consumption patterns due to teleworking get consolidated, introducing an additional factor to be considered when natural gas peak demand needs are evaluated.

6. Conclusion

Understanding European demand behaviour is crucial for policy makers, especially in the current 2022 Ukraine war context, under high risk of supply disruption and potential demand rationing. It will be important to monitored if the EU Commission to reduce natural gas demand have the capacity to modify the current consumption patterns that have been analysed in this article.

Our results suggest that the estimated dynamic elasticities vary significantly at daily and country level, and that natural gas demand has important daily information that we can uncover to obtain estimated elasticities that allow to avoid time aggregation issues when dealing with monthly or lower time frequencies. We show that: *first*, there is a strong seasonal component, mainly due to heating demand, gas price is not a determinant factor for most of the countries. *Second*, we show that Bulgaria, Luxemburg, Poland, the UK, and Portugal are the only exceptions where we find estimated positive own-price elasticities from October to February. These findings have very relevant policy implications regarding price and income measures effectiveness (see also Burns (2021)) to compare our results in Europe with those in the U.S.). Based on our empirical work, we conclude that when policymakers use price-based tools to influence the natural gas demand in Europe, these policies will be more effective during the months from March to August that is where our estimated own-price elasticities present larger values in absolute terms. Moreover, we find that during the months from May to September, most of the analysed EU countries show elastic own-price elasticities, implying that pricing policies (such as taxation, subsidies, or other regulatory tools) will result in a more than proportional reduction in natural gas demand. This knowledge may be very relevant for designing energy policies since the results of those may difference depending on the month of the year. If this fact is not considered and tax mechanisms are not applied to all fossil fuels coherently, the higher elasticity of natural gas during the months from May to September can send the wrong signal to the market and contribute to the use of more polluting alternative fuels, such as coal, jeopardizing part of the potential environmental benefits.

Third and finally, we find that the lockdowns due to covid-19 highly impacted on natural gas demand in all 15 countries confirming the "double heating effect". From the best of our knowledge, our study is the first one in quantifying empirically this effect in the academic literature. The existence of a 'double-heating effect' may have long-term policy implications if new consumption patterns due to teleworking get consolidated, introducing an additional factor to be considered when natural gas peak demand needs are evaluated.

CRediT authorship contribution statement

A.F. Erias: Methodology, Investigation, Software, Formal analysis, Writing, Conceptualization, Writing – review & editing. **E.M. Iglesias:** Methodology, Investigation, Software, Formal analysis, Writing, Conceptualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix

A.1. Literature review

Referring to the literature of the estimation of elasticities of natural gas in countries outside of the EU, Yoo et al. (2009) analysed the case of South Korea with cross-sectional data for the year 2005; Wadud et al. (2011) focused on the case of Bangladesh from 1981 to 2008, Khan (2015) analysed the case of Pakistan from 1978 to 2011; Alberini et al. (2020) considered the case of Ukraine; and using annual data from 1971 to 2009, Kani et al. (2014) studied the case of Iran.

Two countries have obtained an important attention: (1) On one hand we have the case of the USA, where Bloch (1980) provided estimated elasticities and Gautam and Paudel (2018) examined the demand for natural gas in the residential, commercial, and industrial sectors of the North-eastern United States, comprising nine states and using annual state-level panel data over the period between 1997 and 2016. Joutz et al. (2009), Serletis et al. (2010), Alberini et al. (2011), and Payne et al. (2011) also provided the results for the USA using monthly and/or yearly data between 2000 and 2006, 1960 and 2007, 1999 to 2007 and 1970 to 2007; while Dagher (2012) considered the case of Colorado. Burns (2021) has provided estimates of own price and income elasticity of natural gas consumption by residential users in the U.S. from 1970 to 2016. More recently, Joshi (2021) studied the variation of sectoral natural gas demand in the United States using monthly data between 2001 and 2015. Results reveal the inelastic price responses across natural gas consumption sectors and highlight that price-based tools can impact differently on a sectorial basis. (2) The other country that has received an important attention is China (Yu et al., 2014; Sun and Ouyang, 2016; Zhang et al., 2018). For example, Zhang et al. (2018) constructed an autoregressive distributed lag model to estimate the elasticity of natural gas demand in China's various subsectors with yearly data from 1992 to 2015.

A.2. DATA

A.2.1. Daily natural gas consumption

The natural gas consumption data has been extracted from the operational data of the different European Transmission System Operators (TSOs) through either their websites or the transparency portal of the European Network of Transmission System Operators for Gas (ENTSOG).[22] In those countries where there is more than one balancing zone (e.g., Germany), a consolidation of the data was carried out to generate a single value at a national level. Unlike previous works on this matter (e.g. Zhang et al. (2018)), this paper does not provide sectorial segmentation since not all the countries of the sample have this level of disaggregation on a daily basis in the available data sources.

A.2.2. Natural gas prices

Although the European hubs are getting consolidated over time through gradual gains in liquidity and agents, this is not a homogeneous process.[23] For those market in which there is no daily price signal a neighbouring hub was selected as proxy based on the market characteristics (supply and demand).[24]

It is important to highlight the price signals of those organized markets, despite being clear and transparent signals, do not have to reflect the final price to which end consumers (domestic and industrial consumers) are exposed to but the market sentiment about the natural gas price at each moment. Thus, this end price will be determined not only by portfolio of the different suppliers that each country has access to and the pricing formula of the supply contracts (since there is no obligation to link these pricing mechanisms to these hubs[25]) but also by specific taxation and energy policy costs that every country has included in its natural gas bill.

A.2.3. Production in industry index

As explained in Section 4, monthly dataset was transformed into a daily data by generating "bridge" values through a daily compounded growth rate that considers exclusively the working days as described in the equation below:

$$DCRG_i = \left(\frac{HICP_i}{HICP_{i-1}}\right)^{\frac{1}{n}} - 1$$

Being $HICP_i$ and $HICP_{i-1}$ the value of the HICP form the months i and i -1, and n the number of working days in the month i after having discounted Saturday and Sundays and the public holidays.

22 The data from the following countries have been downloaded directly from their TSOs and market areas: Austria (AGGM), Germany (Gaspool and NCG) Italy (SNAM), Portugal (REN), Spain (Enagas), United Kingdom (National Grid). Denmark and France data were retrieved from open data portal. The data from Belgium, Netherlands, Luxembourg, Poland, Croatia, Bulgaria, and Slovenia have been retrieved through ENTSOG transparency portal.

23 For additionally information see OIES' work on the matter (Heather, 2012, 2019a,b, 2020).

24 A proxy was needed for the following markets: Portugal (MIBGAS); Luxembourg and Denmark (TTF); Poland (NCG/GPL); Bulgaria, Croatia, and Slovenia (PSV).

25 Contracts with oil-indexed pricing formulas are still dominant despite gas hub-linked pricing continues to grow as new contracts are signed and legacy oil-linked contracts expire IEA, 2020a,b.

Table 7
Indicators used for stringency index.

Indicator	*Max. Value (N_j)*	*Flag (F_j)*
C1 – School closing	*3 (0, 1, 2, 3)*	*Yes = 1*
C2 – Workplace closing	*3 (0, 1, 2, 3)*	*Yes = 1*
C3 – Cancel public events	*2 (0, 1, 2)*	*Yes = 1*
C4 – Restrictions on gathering size	*4 (0, 1, 2, 3, 4)*	*Yes = 1*
C5 – Close public transport	*2 (0, 1, 2)*	*Yes = 1*
C6 – Stay at home requirements	*3 (0, 1, 2, 3)*	*Yes = 1*
C7 – Restrictions on internal movement	*2 (0, 1, 2)*	*Yes = 1*
C8 – Restrictions on international travel	*4 (0, 1, 2, 3, 4)*	*No = 0*

Once this compound growth rate was obtained, a daily value was generated either by applying it to the previous value in case of a working-day or maintaining the value of the previous day if non-working-day. This transformation has been done in a way that the values at the end of the month matches the original values for the month of the monthly dataset.

A.2.4. Stringency index

The Stringency Index was defined using the database and the methodology developed by the Blavatnik School of Government, reformulating the index to limit the categories included to the Containment and closure indicators. As stated in Hale et al. (2020, page 26), the indicator is "*a simple average of the individual component indicators. This is described in Eq. (2) below where k is the number of component indicators in an index and Ij is the sub-index score for an individual indicator*".

$$Index = \frac{1}{k}\sum_{j=1}^{k} I_J \tag{2}$$

To determine the subindices included to generate the general index, we selected exclusively those whose effects could potentially be more relevant to the gas demand or the patterns of consumption. All the indicators analysed are specified in the Table 7:

As described in Hale et al. (2020, pages 27 and 28), "*each sub-index score (I) for any given indicator (j) on any given day (t), is calculated by the function described in Eq. (2) based on the following parameters:*

- *the maximum value of the indicator (Nj).*
- *whether that indicator has a flag (Fj = 1 if the indicator has a flag variable, or 0 if the indicator does not have a flag variable)*
- *the recorded policy value on the ordinal scale (vj,t)*
- *the recorded binary flag for that indicator, if that indicator has a flag (fj,t)*"

$$I_{j,t} = 100\frac{v_{j,t} - 0,5(F_j - f_{jt})}{N_J}$$

A.3. Results

As seen in Table 3, cross-price elasticities between natural gas and coal are only statistically significant for three countries (Austria, Portugal, and the United Kingdom) of our sample, presenting different signs and values. As highlighted by Serletis et al. (2011), the characteristics of each country (e.g. energy mix, economic activity etc.) determine if coal and natural gas are either complementary (as shown in Table 3 in Portugal) or substitutive (as shown in Table 3 in Austria, and the United Kingdom), not being determinant the level of economic development. As mentioned above, we argue that Portugal's results are linked to the fast path reducing role of coal in the energy mix, going from representing almost 24% of the power generation

Table 8
Estimated long-run effects for HDD and CDD.

Long-run effects	Estimated value
HDD	0.0133463
CDD	−0.0391645

mix in 2016 to 2.6% in 2020. Portugal has accelerated its coal phase-out plans, initially expected to 2023, closing Sines power plant (1180 MW) in January 2021 and Pego (576 MW), its last coal power plant, in November 2021. Portugal will become the fourth country to phase out completely coal power generation, following Belgium (2016), Austria (2020), and Sweden (2020). Five more European countries have closing plans for the coal power generation: France (2022), Slovakia (2023), the UK (2024), Ireland (2025), and Italy (2025). Paradoxically, the other two statistically significant countries (Austria and the United Kingdom) where we find that coal and natural gas are substitutive goods in Table 3 (see e.g. Loureiro et al. (2013) for a review about benefits from low-carbon fuels), have plans to close their generation (one recently executed in 2020, and another planned for 2024).

In Table 3, cross-price elasticities between natural gas and CO_2 are only statistically significant for two countries (Austria and Croatia) presenting signs and values coherent with what should be expected. CO_2 prices play a crucial role on the switching process from coal to natural gas, especially in power sector, internalizing CO_2 emissions cost in both technologies variable cost functions, modifying the merit order for dispatching, and determining the competitiveness of one against the other.

Finally, in relation to the climatic variables, we computed Table 8 from the results of Table 3, where Heating Degree Days (HDD) has been shown to be statistically significant in our analysis with a positive effect on gas demand. Our results in Table 8 are fully aligned with the existing literature, suggesting that each additional HDD generates an increase of 1.37% increase of the daily gas consumption. On the contrary, Cooling Degree Days (CDD) has a negative effect on daily gas consumption, generating 3.94% reduction per additional CDD. The CDD sign does not match up with the results obtained by Labandeira et al. (2012) for the electricity demand. Electricity demand is expected to have a different behaviour than for natural gas demand since most of climatization systems rely on electricity to be boosted. However, the impacts on gas demand go in both directions in our Table 3. There is a direct negative impact on gas consumption from fewer heating needs and an indirect positive impact, potentially coming from a higher power demand but only if gas natural generation increases to meet that additional power demand. We argue that this direct negative impact is higher than the potentially positive effect resulting in an overall negative effect.

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