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Project thesis

Estimating elasticities of residential natural gas demand in Europe

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Abstract

In this paper, we examine the residential natural gas demand for a panel of 13 EU countries from 1979 to 2020, representing 90% of the household's consumption in the region. Using the mean group estimator on autoregressive distributed lag specifications, we estimate natural gas demand in Europe and its relationship with natural gas price, income and weather. Our results show an inelastic long-run price elasticity of -0.399 and a long-run income elasticity of 0.892. In the short run, only weather is found to impact demand. These findings have important implications for policy makers both in the transition to a low-carbon energy system and in addressing current issues related to security of supply.

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1 Introduction

Natural gas accounts for 24% of the EU energy mix (Eurostat, 2022b) and continues to be an essential energy source for power generation and heating in the region.

The European Green Deal sets a goal of achieving net-zero emissions by 2050, which requires a major transition in the energy system. In this context, the way consumers respond to price changes of fossil fuels will impact the effectiveness of energy policies like carbon taxes and quotas. To achieve the necessary emissions reductions, policy makers need a better understanding of these dynamics and design policies accordingly.

In the short run, security of supply has now become the key concern in European energy policy. The REPowerEU plan (European Commission, 2022) aims to quickly reduce exposure to Russian natural gas imports, which reached 155 billion cubic meters (bcm) in 2021. However, Fulwood and Hall (2022) have characterized the diversification strategy as "extremely challenging", highlighting the importance of demand-side measures for a successful phase-out of Russian natural gas. One such measure is the "EU Save Energy Communication", which relies on changes in consumer behaviour to save around 13 bcm of gas. The uncertainty regarding how consumers will respond to these new conditions remains high.

Despite the urgent need for insights into the demand response of natural gas, few elasiticity estimates have been provided in the literature in recent years. Asche et al. (2012) evaluate elasticities of residential natural gas demand using a broad set of estimators, but neglect the well-known problem of spurious regression with non-stationary data. Bernstein and Madlener (2011) address this issue in a working paper by using the Autoregressive distributed lag (ARDL) cointegration approach, but do not take advantage of the panel structure despite the short time series.

This paper examines the residential natural gas demand for a panel of 13 EU countries, together representing 90% of the sector's consumption in the region. Using the ARDL cointegration approach, we model natural gas demand as dependent on its own past values as well as the contemporaneous and lagged values of price, income and weather. Through the properties of the ARDL model, we address the spurious regression issue without losing information on the long-run relationship. By allowing the dynamic structure to vary cross-sectionally, we account for different consumer behaviours across countries. Finally, through the use of the mean group estimator, we seek to increase the robustness of a Europe-wide estimate of demand elasticities.

2 Literature review

Determining how consumers adjust their energy consumption in response to price changes has long been a central question in energy economics. The studies estimating energy elasticity of demand dates back to last century. Houthakker (1951) is among the earliest efforts, examining electricity demand in the United Kingdom from 1937-1938, introducing a loglinear model regressing electricity consumption on household income, marginal price of electricity, marginal price of a substitute and average holdings of heavy domestic equipment. Dahl (1993) discusses the fact that the stock of energy appliances may be unavailable, a challenge to such studies. Houthakker and Taylor (1970) and Balestra and Nerlove (1966) develop model specifications that overcome the issue of non-availability of the stock. Balestra and Nerlove (1966) were pioneers in utilizing the panel data structure, estimating elasticity of demand in the US with a pooled aggregated panel, with which they obtain a long-run estimate of -0.63. Another classical study is that of Pindyck (1979), introducing a structural form model, based on the demand of energy services (lighting, heat and power), rather than energy itself. Studying the structure of energy demand for various fuels in 9 OECD countries, he finds an estimate of the long-run price elasticity of demand of -1.7 for natural gas.

In our literature search, we found that the amount of publications on the topic of energy elasticities dropped distinctly after the 1980s, with an increase during the last 15 years.

As exhibited in Table 1 the estimates of price elasticity of demand varies greatly across studies. Our selected literature make use of different modelling techniques at different aggregation levels. In a meta analysis Labandeira et al., 2017 find an average price elasticity of natural gas of -0.180 in the short run and -0.684 in the long run across the selected empirical literature. It seems that studies analyzing country-aggregated data have a different econometric approach and understanding of the fundamental challenges to estimation, than those who use micro-level data.

Table 1: Literature review

Study	Countries	Data	Price elasticity of demand: Short run	Long run
Asche et al. (2012)	12 European countries	Annual cross section: 1978-2002	-0.1 to 0	-0.6 to 0
Auffhammer and Rubin (2018)	California, US	Monthly residential bills 2010-2014	-0.23 to -0.17	-
Labandeira et al. (2017)		230 natural gas studies	-0.180	-0.684
Pindyck (1979)	9 OECD countries	Annual cross-section 1960-1974	-	-1.7
Balestra and Nerlove (1966)	36 US states	Pooled panel 1957-1962	-	-0.63
Alberini et al. (2011)	US	Monthly residential bills 1997-2007	Dynamic: -0.572	-0.647
Dagher (2012)	Colorado, US	Monthly utility data 1994-2006	-0.091	-0.235
Alberini et al. (2020)	Ukraine	Monthly residential bills 2013-2017	-0.16	-
Bernstein and Madlener (2011)	12 OECD countries	Annual cross section: 1980-2008	-0.24	-0.51
Liu (2004)	23 OECD countries	Annual panel 1978-1999	-0.102	-0.364
Burke and Yang (2016)	44 countries	Annual 1978-2011	-1.43 to -0.13	-1.25

2.1 Studies on region-level data

The study of Asche et al. (2012) formulates a log-linear dynamic demand model in the tradition of Houthakker and Taylor (1970) to analyze natural gas demand in 12 European countries. Their specification includes variables for price of natural gas, price of substitutes, disposable income and heating degree days to account for weather conditions. They argue that there probably are large structural differences in residential gas consumption between European countries, and discuss the appropriateness of homogeneous type estimators compared to individual cross-section regression models. They claim that the latter often provide implausible estimates, with fewer degrees of freedom, whereas the homogeneous type might lead to loss of information, missing potential structural differences between cross-sections. This discussion has also been important for our work. Their solution is the shrinkage estimator suggested by Maddala et al. (1997), shrinking country-specific parameters towards a common probability distribution. They find a price elasticity of -0.10 to 0 for the short run, and -0.06 to 0 for the short run.

Non-stationarity is a fundamental issue of time series that has only recently been addressed in the literature of elasticities of energy demand. The presence of non-stationary series may lead to spurious regression, suggesting a causal relationship between the variables, when the results should rather be interpreted as evidence of contemporaneous correlation (Brooks, 2014). There might also be a cointegrating relationships between the non-stationary variables, as introduced in the seminal paper of Engle and Granger (1987). Ever since, cointegration analysis has been a well-known econometric technique. However, very few papers in our selected literature considers the possibility of non-stationarity of the time series. Only Dagher (2012) and Bernstein and Madlener (2011) discuss and tests for unit roots, all using regionally aggregated data.

Both Dagher (2012) and Bernstein and Madlener (2011) goes on to estimate an autoregressive distributed lag (ARDL)-model, a dynamic model containing lags of both explanatory and explained variables. Bernstein and Madlener (2011) argues that the advantage of this approach is that information on the exact order of integration of the variables is not needed in advance. One only needs to test for the fact that a long-run relationship exists in the data, through the ARDL bounds testing procedure. Dagher (2012) analyse the demand of natural gas in Colorado, US from 1994 to 2006, and find a price elasticity of demand of -0.091 and -0.235 in the short and long run respectively through the ARDL approach. Bernstein and Madlener (2011) study 12 OECD countries from 1980-2008, modelling an ARDL for each country, obtaining an elasticity of demand of -0.24 in the short run and -0.51 in the long run.

2.2 Studies on micro-level data

Analyzing residential demand on a micro-level data set enables researchers to match consumers with the price they face, and also allows for research into heterogeneity across consumers.

In the micro context, consumers may face tiered pricing regimes. In such a setting, the price reaching the end user would be a mechanical function of the quantity it consumes, and hence it would be unreasonable to assume that price is exogenous (Auffhammer & Rubin, 2018). Where the aggregated studies discuss the issue of stationarity, the recent micro-level literature discuss another fundamental issue in estimating elasticities of demand: the simultanous determination of price and consumption. As of classic economic theory, the market price is determined by supply and demand factors, in equilibrium.

To overcome the challenge of endogenous variables, the studies of Alberini et al. (2020) and Auffhammer and Rubin (2018) make use of the instrumental variable (IV)-approach. Using variables that are correlated with price, but not with demand, they run a regression on price as a first step, using the fitted values for price in the final estimation.

Auffhammer and Rubin (2018) studies natural gas consumption in California using a micro level dataset, obtained by analyzing 300 million residential energy bills. In addition to the IV approach, they make use of spatial discontinuity between two natural gas utilities, which they argue make up an arbitrary border within-city. Assuming that the households characteristics across the utility border are equal, they argue that the one group can be used as a control, when the two utility regions are exposed to different prices. They find a short-run price elasticity of demand for natural gas of in the range -0.21 to -0.17.

Alberini et al. (2020) studies the demand response following large variations in price in the Ukraine between 2013 and 2017. Obtaining information from the natural gas bills of 514 households, they find a short run elasticity of demand of -0.16.

Several studies such as the meta analysis of Labandeira et al. (2017) and Bohi (1981) notes that studies with disaggregated data has been shown to produce lower elasticity estimates in absolute terms.

3 Data

The collected data represents yearly natural gas residential demand, prices, household income and weather conditions at country level. Although such time series exist for all EU countries, we require more than 25 complete observation sets to obtain meaningful estimates. After the data processing described below, we are left with an unbalanced panel of individual length $T_i \in [26, 42]$ within the period 1979-2020 for $N = 13$ groups: Austria (AUT), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), France (FRA), Hungary (HUN), Ireland (IRL), Italy (ITA), Luxemburg (LUX), Netherlands (NLD), Poland (POL) and Slovakia (SVK). Together, these countries represent 90% of the natural gas demand from households in the EU[1].

3.1 Price and demand data

The International Energy Agency (IEA) publishes datasets for both fuel specific energy consumption and prices. To sample household demand for natural gas, we collect the residential final consumption flow in the *World Energy Balances* published by (IEA, 2022c). The prices paid by households for natural gas and its substitutes are retrieved from *Energy prices in national currency per toe* (IEA, 2022a). To reflect the actual end-user prices, VAT and other taxes are included in this metric.

Figure 1 shows the demand differences in both levels and trends between countries. We see a demand increase for most countries until the turn of the millennium, a period where important natural gas infrastructure was developed. On Figure 2, we also observe falling prices in that period, especially from the mid-80's.

Some of the structural breaks in the time series of demand are due to changes in in the underlying data collection or reporting methods. For example, IEA (2022d) reports such changes around 2000 for Luxembourg and 1990 for France, which may explain the level shifts observed at those points. We therefore include dummy variables in the analysis, assuming that the effect of the changes is constant before and after the break and that the magnitude of the effect can be captured by a single dummy. This allows us to obtain more accurate estimates despite the presence of level shifts.

Figure 2 also illustrates how time series for price suffer from gaps with missing ob-

[1] Estimate based on IEA (2022b) consumption data for the residential sector in 2020, including the EU-27 aggregate and at national level for the countries listed.

servations. Since IEA only describes their methodology for prices in general terms, we are unable to determine the cause of the gaps or recover the missing data. To address this issue, we use linear interpolation to impute the missing price observations rather than discarding all the observations for that year. While this may introduce a small bias into the model, it also helps to reduce the finite sample bias that is inherent in dynamic models when using a limited number of observations. In the case of Belgium, we choose not to go further in estimating a model as the gap is too large to give plausible results.

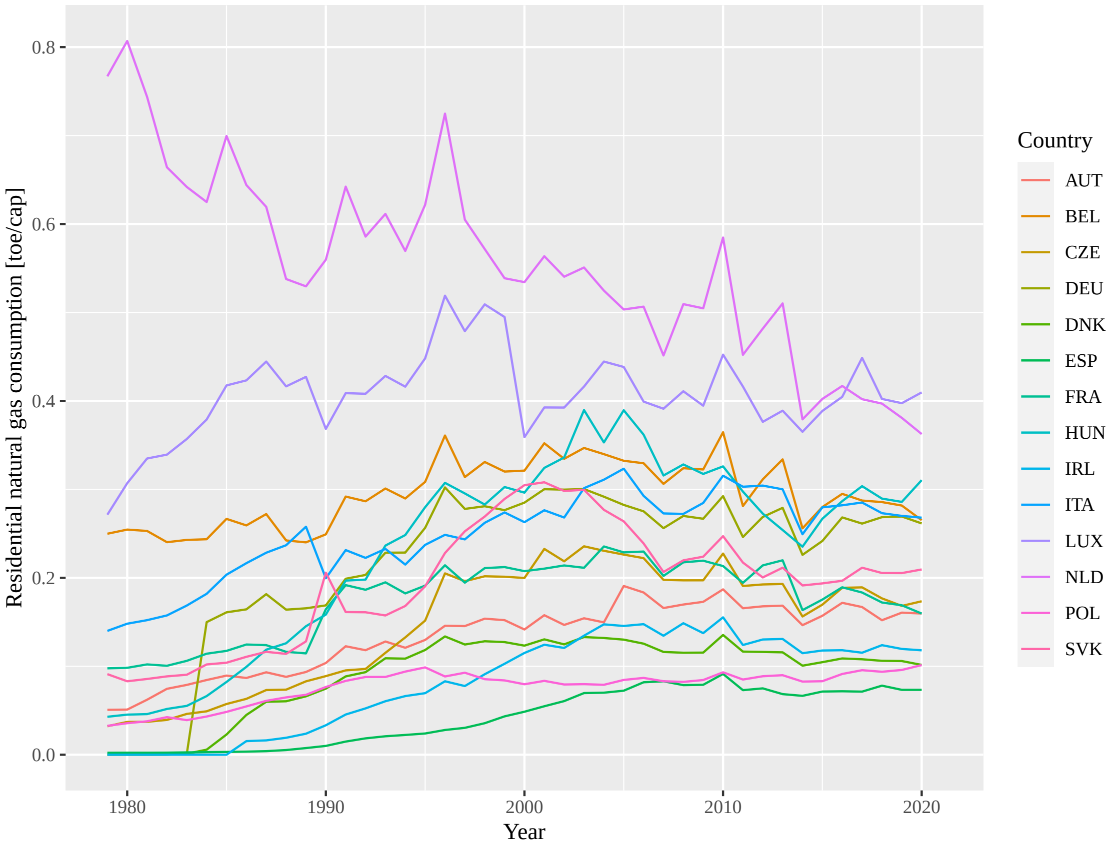

Figure 1: Final consumption of natural gas in the residential sector (IEA, 2022c), per capita (The World Bank, 2022b).

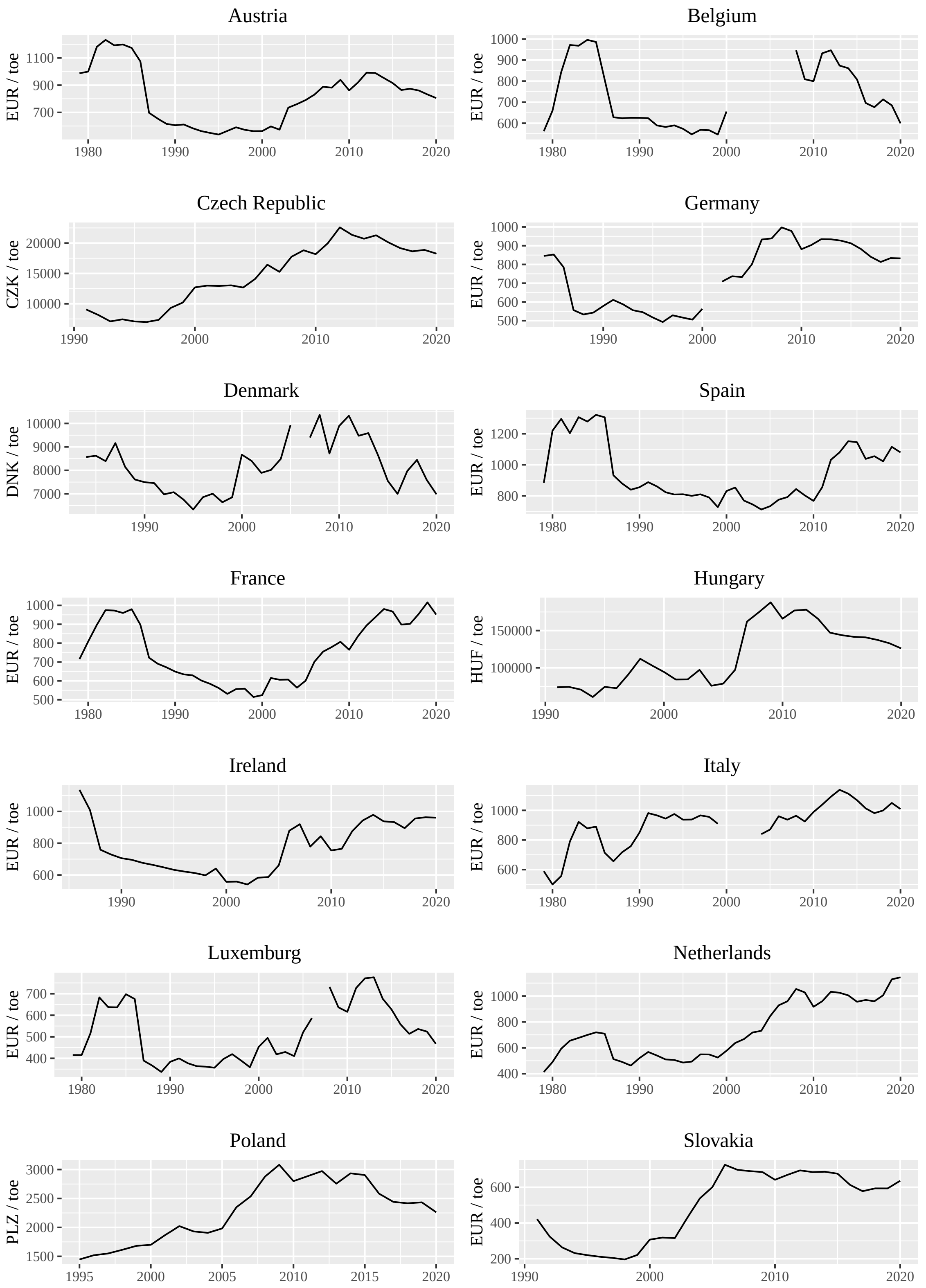

Figure 2: Price of natural gas served to households including VAT and other taxes (IEA, 2022a), per capita (The World Bank, 2022b), deflated with CPI (OECD, 2022a).

3.2 Income data

We use *"household and non-profit institutions serving households (NPISH) consumption expenditure"* provided by The World Bank (2022a) as a proxy for disposable income. This is motivated by the fact that the time series for explicit household income data reported by OECD (2022b) is short, with most countries lacking data before 1995. A basic requirement for a proxy is to be correlated with the variable of interest. We infer from Figure 3 that consumption expenditure and income are closely correlated, suggesting the proxy is suitable.

Since the disposible income data we want to approximate is presented in nominal Purchasing Power Parity (PPP)-adjusted dollars per capita, the expenditure data must be transformed accordingly before the correlation estimation. Like for demand, we divide by population to obtain per capita values. Nominal prices adjusted with PPP rates from OECD (2022c) are used for the income correlation estimation, but deflated local currency values are used in the remaining analysis in line with natural gas prices.

Developments in household consumption expenditure is shown in Figure 4, which indicate substantial growth in wealth for all countries in the sample period. It is worth noting a trend break for most countries following the financial crisis, leading to poorer income development in recent years. We also observe an income shock in the pandemic year of 2020 for all countries.

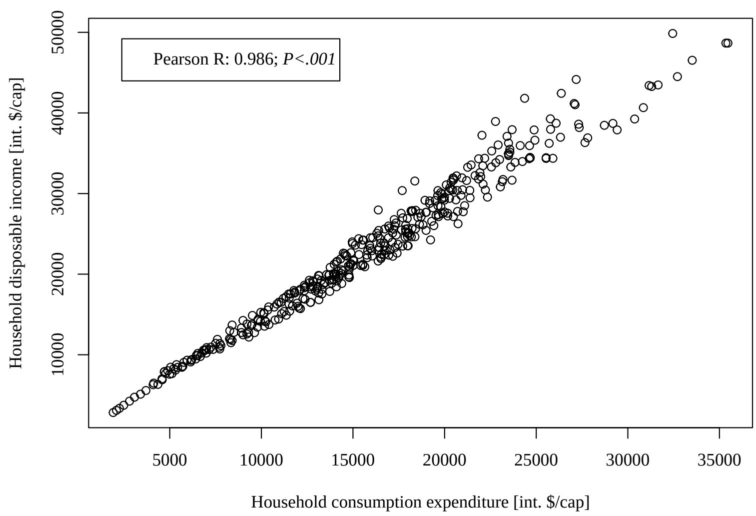

Figure 3: Scatter plot showing the correlation between household consumption expenditure (The World Bank, 2022a) and household disposable income (OECD, 2022b).

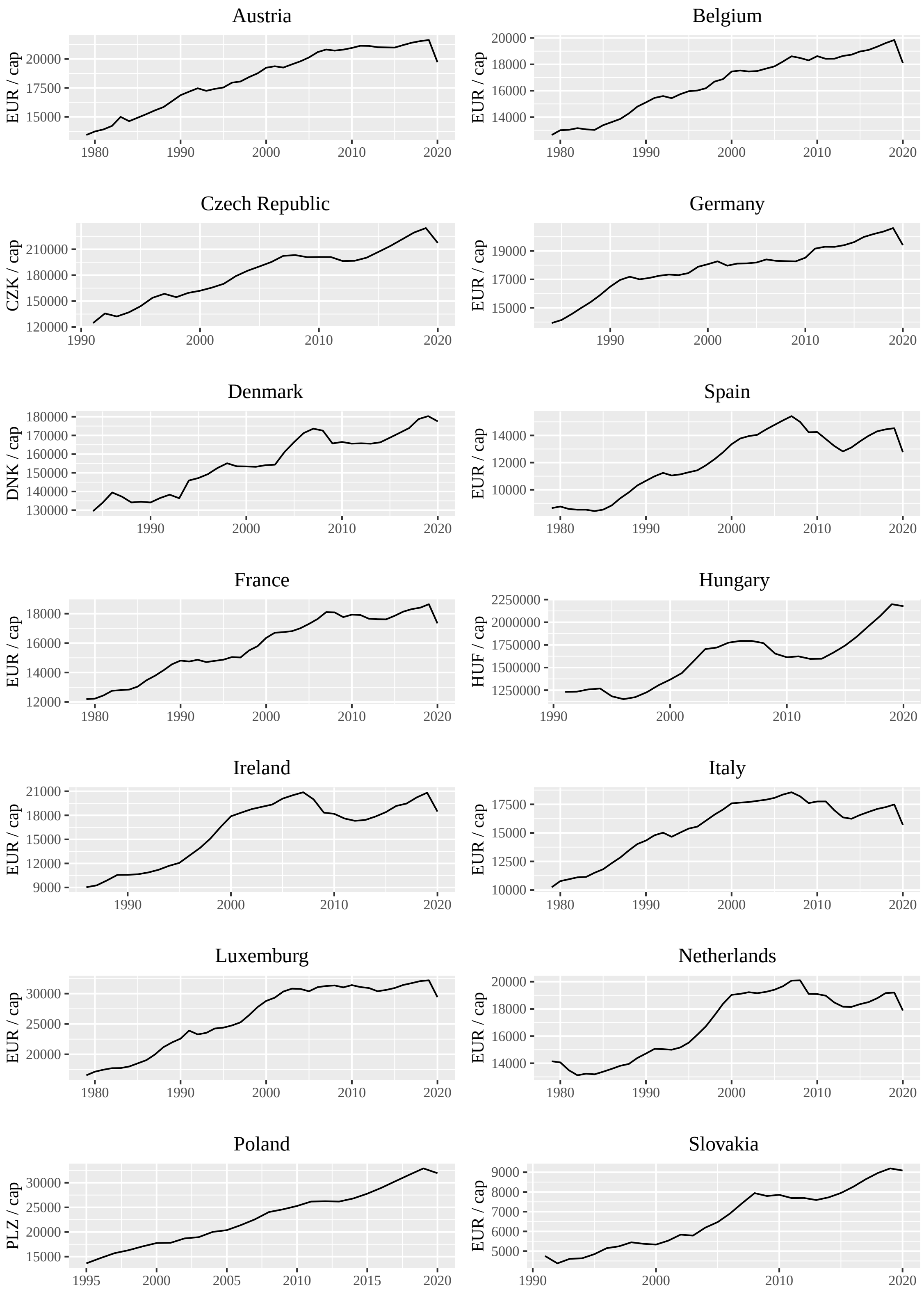

Figure 4: Households and NPISHs final consumption expenditure (The World Bank, 2022a), per capita (The World Bank, 2022b), deflated with CPI (OECD, 2022a).

3.3 Weather data

To describe the weather-driven variations in needs for natural gas, we collect heating degree days (HDD) from Eurostat (2022a). They calculate daily HDDs with Eq. 1, where $\bar{T}_{i,d}$ is the mean temperature for day d. Figure 5 shows the yearly HDD totals $W_{it} = \sum_{d=1}^{365} HDD_{i,d}$ for each country i. We see large cross-sectional variations in the need for heating, but with a conspicuous negative trend for all countries due to rising winter temperatures.

$$HDD_{i,d} = \begin{cases} 18\,°\mathrm{C} - \bar{T}_{i,d} & \text{if } \bar{T}_{i,d} \leq 15\,°\mathrm{C} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

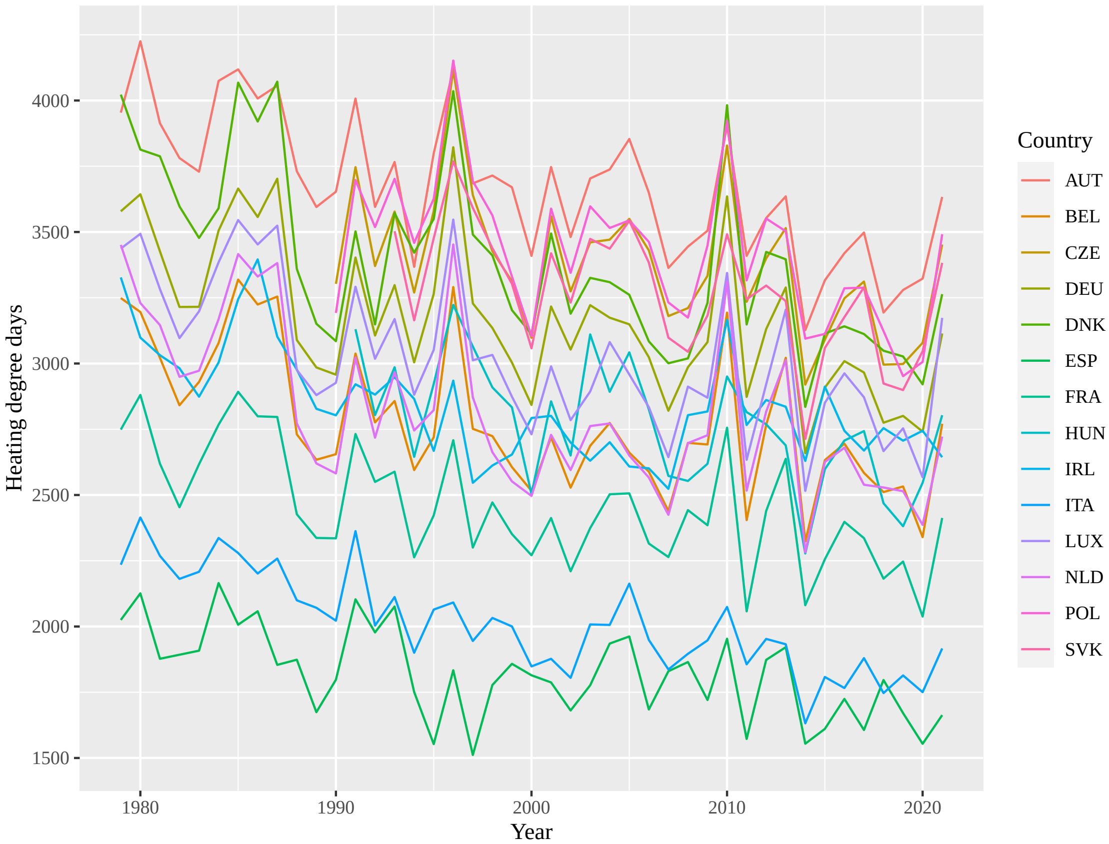

Figure 5: Heating degree days for countries analyzed (Eurostat, 2022a).

Table 2: Summary statistics

Variable	Country	Obs	Mean	St. dev	Min	Max	Unit of measurement
Demand	AUT	42	133.55	38.91	50.76	190.76	kgoe/capita
	BEL	35	286.46	34.63	240.08	364.59	
	CZE	30	186.00	37.55	95.36	235.63	
	DEU	37	246.45	46.96	149.93	302.22	
	DNK	37	103.58	31.22	5.73	135.41	
	ESP	34	52.28	27.49	4.04	91.35	
	FRA	42	175.92	43.55	97.71	235.45	
	HUN	30	296.25	46.79	196.87	389.64	
	IRL	35	99.44	42.90	15.38	155.32	
	ITA	38	245.90	49.70	140.00	323.37	
	LUX	42	406.80	48.48	271.33	518.95	
	NLD	42	553.98	108.25	362.53	806.88	
	POL	26	87.41	6.26	79.05	101.36	
	SVK	30	226.91	44.81	157.45	308.02	
Price	AUT	42	813.59	211.80	537.48	1,232.36	EUR/toe
	BEL	35	728.16	151.63	546.21	995.83	EUR/toe
	CZE	30	14,620.72	5,167.08	6,988.36	22,594.49	CZK/toe
	DEU	36	739.98	170.38	492.73	997.81	EUR/toe
	DNK	36	8,146.89	1,111.90	6,330.40	10,366.07	DNK/toe
	ESP	34	883.19	130.54	712.05	1,151.93	EUR/toe
	FRA	42	756.53	163.07	514.44	1,016.32	EUR/toe
	HUN	30	117,526.82	39,978.61	60,697.88	187,987.45	HUF/toe
	IRL	35	771.35	160.51	540.26	1,136.10	EUR/toe
	ITA	38	904.90	150.54	499.62	1,138.78	EUR/toe
	LUX	41	513.46	134.41	336.68	776.33	EUR/toe
	NLD	42	736.22	222.72	413.43	1,144.76	EUR/toe
	POL	26	2,286.62	526.41	1,446.51	3,082.14	PLZ/toe
	SVK	30	488.99	195.07	196.02	725.80	EUR/toe
Income	AUT	42	18,375.57	2,566.82	13,433.63	21,638.64	EUR/capita
	BEL	35	16,257.18	2,332.61	12,645.10	19,844.98	EUR/capita
	CZE	30	182,390.83	30,616.02	124,614.78	234,502.85	CZK/capita
	DEU	37	17,804.15	1,691.59	13,929.26	20,610.17	EUR/capita
	DNK	37	155,786.01	15,275.72	129,516.30	180,318.18	DNK/capita
	ESP	34	12,910.08	1,660.54	9,373.82	15,421.35	EUR/capita
	FRA	42	15,818.45	2,033.47	12,189.69	18,643.15	EUR/capita
	HUN	30	1,589,952.46	301,873.10	1,151,034.08	2,199,205.71	HUF/capita
	IRL	35	16,072.78	3,931.86	9,031.50	20,877.81	EUR/capita
	ITA	38	15,247.01	2,516.56	10,239.12	18,558.09	EUR/capita
	LUX	42	26,161.08	5,331.16	16,543.43	32,190.20	EUR/capita
	NLD	42	16,866.20	2,414.19	13,115.24	20,100.44	EUR/capita
	POL	26	22,994.20	5,712.66	13,635.40	32,910.45	PLZ/capita
	SVK	30	6,676.91	1,525.65	4,379.41	9,194.92	EUR/capita
Weather	AUT	42	3,669.48	271.21	3,126.98	4,225.38	Heating degree days
	BEL	35	2,811.48	284.25	2,323.21	3,319.10	
	CZE	30	3,374.27	264.26	2,919.87	4,116.32	
	DEU	37	3,137.41	284.43	2,659.00	3,822.29	
	DNK	37	3,344.76	328.24	2,834.98	4,071.66	
	ESP	34	1,780.45	151.67	1,511.54	2,103.43	
	FRA	42	2,456.48	223.80	2,037.95	2,892.35	
	HUN	30	2,769.62	231.33	2,277.68	3,222.79	
	IRL	35	2,797.26	179.90	2,523.35	3,395.82	
	ITA	38	2,028.92	189.81	1,631.87	2,414.40	
	LUX	42	3,025.35	278.56	2,515.66	3,547.24	
	NLD	42	2,820.70	314.23	2,282.08	3,452.64	
	POL	26	3,405.18	280.41	2,951.82	4,151.88	
	SVK	30	3,285.56	241.32	2,713.17	3,768.25	

4 Econometric method

In line with the ad-hoc approach to energy demand estimation proposed by Houthakker and Taylor (1970), we assume that the log-transformed natural gas demand function in the long run for each country i takes the form

$$D_{it} = \eta_{1i} P_{it} + \eta_{2i} Y_{it} + \eta_{3i} W_{it} \tag{2}$$

where D_{it} is the logarithmic equilibrium demand in year t, explained by the log-transformed variables price P_{it}, income Y_{it} and weather W_{it}. The corresponding coefficients $\eta_{1i}, \eta_{2i}, \eta_{3i}$ represent the constant long-run elasticities to be estimated.

4.1 Unit root testing

The presence of non-stationary variables could lead to spurious results, driving misleading conclusions about the variables. However, if the data series are in fact non-stationary, and there exists a cointegrating relationship between them, it would also allows us to examine the long-run relationship between the variables, such as long run price elasticity of demand, increasing our understanding of how consumers act when prices change.

The unit root tests of Dickey-Fuller and Phillips-Perron are commonly used, but are also known to suffer from low power when a stationary data generating process is close to $I(1)$ (Brooks, 2014).

Maddala et al. (1997) and Brooks (2014) argue that panel unit root tests have increased power compared to unit root tests based on a single time series. We investigate different panel-based alternatives for testing, all with the null hypothesis of non-stationarity against the alternative of stationarity in the panel data.

The panel unit root tests build on the Adjusted Dickey-Fuller test, first introduced by Dickey and Fuller (1979).

$$\Delta y_{i,t} = \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \theta_{ij} \Delta y_{i,t-j} + \alpha_i + \varepsilon_{i,t} \tag{3}$$

If the time series is stationary and mean-reverting, last periods value y_{t-1} in Eq. 4.1 The panel unit root tests employ the null hypothesis $H_0 : \rho_i = 0$ (no explaining power) against the alternative hypothesis $H_a : \rho < 0$ (mean-reversion) for all groups $i = 1, 2, ...N$

The three panel root tests represent different methods to combine the cross-sectional test results.

- Levin et al. (2002) develop unit root tests for panels building on the ADF-test, incorporating both a time trend and an individual time and specific effect. Their null hypothesis is that all individual time series in the panel contain a unit root, while under the alternative, all individual series are stationary. The Levin and Lin-test assumes that all series must be integrated of the same degree, which could be a strong assumption.
- Im et al. (2003) (IPS) relax the assumption that $\rho_1 = \rho_2 = ... = \rho_N$ under H_a. The test conducts separate unit root tests for the N cross-sectional units, combining the evidence of the unit root hypothesis using the test statistics. The IPS is a parametric and asymptotic test.
- Maddala and Wu (2002) allow for an unbalanced panel. Where the IPS test combines test statistics, the Maddala Wu test combines the significance levels of the individual tests, assuming that the significance levels follows a chi-squared distribution. In contrast to IPS, it is non-parametric, and p-values are derived by Monte Carlo simulation.

We perform and compare these three tests in order to improve the power of our testing procedure, reported in Table 3.

4.2 Autoregressive distributed lag (ARDL) model

The dynamics of the demand function in Eq. 2 can for each country i be modeled with an ARDL($p_i, q_{1i}, q_{2i}, q_{3i}$) specification that contains lags of both the explained and explanatory variables:

$$D_{it} = \sum_{l=1}^{p_i} \alpha_{li} D_{i,t-l} + \sum_{l=0}^{q_{1i}} \beta_{1i,l} P_{i,t-l} + \sum_{l=0}^{q_{2i}} \beta_{2i,l} Y_{i,t-l} + \sum_{l=0}^{q_{3i}} \beta_{3i,l} W_{i,t-l} + \omega_i + \nu_t \quad (4)$$

Where ω_i is the country-specific fixed effects term and ν_t is an i.i.d error term.

To perform the ARDL bounds test for cointegration, we reparameterize the ARDL model to an unrestricted error correction model (ECM)[2]:

$$\begin{aligned}\Delta D_{it} = &\sum_{l=1}^{p_i-1} \phi_{li}\Delta D_{i,t-l} + \sum_{l=0}^{q_{1i}-1} \theta_{1li}\Delta P_{i,t-l} + \sum_{l=0}^{q_{2i}-1} \theta_{2li}\Delta Y_{i,t-l} + \sum_{l=0}^{q_{3i}-1} \theta_{3li}\Delta W_{i,t-l} \\ &+ \rho_i D_{i,t-1} + \pi_{1i}P_{i,t-1} + \pi_{2i}Y_{i,t-1} + \pi_{3i}W_{i,t-1} + \varepsilon_{it} + \omega_i + \nu_t\end{aligned} \tag{5}$$

To see if there is a long-run relationship between the variables, we conduct the bounds F-test proposed by Pesaran et al. (2001). The properties of the underlying ARDL specification ensure the bounds test to give consistent results even when the variables have different order of integration $\mathrm{I}(d), d < 2$. In the first step, we estimate the coefficients of Eq. 5 using OLS. Then we conduct a F-test, with the null hypothesis of no cointegrating relationship between the variables and the alternative of one cointegrating vector:

$$H_0 : \rho_i = \pi_{1i} = \pi_{1i} = \pi_{2i} = \pi_{3i} = 0 \tag{6}$$

$$H_a : \rho_i \neq \pi_{1i} \neq \pi_{1i} \neq \pi_{2i} \neq \pi_{3i} \neq 0 \tag{7}$$

The test statistic is compared against a set of critical value bounds for the two extreme cases where all variables are $I(0)$, the lower bound, and where all are $I(1)$, the upper bound. If the calculated F-statistic is above the upper bound, the null hypothesis of no cointegrating relationship is rejected, whereas if the F-statistic is within the critical value band, the test is inconclusive.

Narayan (2005) points out that the conventional critical values provided by Pesaran et al. (2001) are invalid for short time series and calculates a new set of critical values for sample sizes ranging from 30-80. Therefore, we use the critical values reported by Narayan (2005) which are more suitable for our sample sizes.

If cointegration exists, we can further reparameterize Eq. 5 to a restricted ECM:

[2] For the interested reader, the EViews team (IHS Global Inc., 2017) provides an excellent explanation of the algebraic steps involved in reparametrizing the ARDL representation to different variants of the ECM.

$$
\begin{aligned}
\Delta D_{it} = & \sum_{l=1}^{p_i-1} \phi_{li} \Delta D_{i,t-l} + \sum_{l=0}^{q_{1i}-1} \theta_{1li} \Delta P_{i,t-l} + \sum_{l=0}^{q_{2i}-1} \theta_{2li} \Delta Y_{i,t-l} + \sum_{l=0}^{q_{3i}-1} \theta_{3li} \Delta W_{i,t-l} \\
& + \rho_i EC_{i,t-1} + \omega_i + \nu_t
\end{aligned} \tag{8}
$$

where the error correction term $EC_{i,t} = D_{i,t} - (\eta_{1i} P_{i,t} + \eta_{2i} Y_{i,t} + \eta_{3i} W_{i,t})$ represents the cointegrating relationship, where $\eta_{\mathbf{i}} = \pi_{\mathbf{i}} / - \rho_{\mathbf{i}}$. Notice that in equilibrium where all difference terms are zero, Eq. 8 will reduce to our long-run function in Eq. 2. Hence, $\eta_{\mathbf{i}}$ are the long-run elasticity coefficients, while ρ_i is interpreted as the speed of adjustment toward that long-run equilibrium. For convergence, ρ_i must be negative, significant and less than unity in amplitude.

4.3 Panel estimators

The next step after finding evidence of a long-run relationship is to estimate the panel ECM specified in Eq. 8. For doing this, we examine three different estimators that allow for varying levels of cross-sectional heterogeneity between groups.

The least restrictive one is the Mean Group (MG) estimator (Pesaran & Smith, 1995), where all parameters are estimated separately and then averaged. Applied to Eq. 8, this will give

$$
\begin{aligned}
\bar{\phi_l} = & \frac{1}{N} \sum_{i}^{N} \phi_l, \quad \bar{\theta_{kl}} = \frac{1}{N} \sum_{i}^{N} \theta_{kl}, \quad \bar{\rho} = \frac{1}{N} \sum_{i}^{N} \rho_i, \quad \bar{\omega} = \frac{1}{N} \sum_{i}^{N} \omega_i, \\
& \forall \quad k = 1,2,3 \quad l = 1,2,...
\end{aligned} \tag{9}
$$

where $\bar{\eta}$ measures the 'average' long-run effect of price, income and weather on demand. Similarly, we can obtain the short-run multiplier interpreted as the contemporaneous impact of each of the exogenous variable price, income and weather (here denoted x) on demand:

$$
m_{sr} = \frac{\partial D_t}{\partial x} = \frac{\bar{\theta_0}}{-\bar{\rho}} \tag{10}
$$

where $\bar{\theta_0}$ represents the mean coefficient of the time t difference for the corresponding variables in Eq. 8.

Following Frank (2007), we estimate the standard errors of the MG coefficients with Eq. 11:

$$\hat{SE}_{MG} = \sqrt{\frac{1}{N(N-1)} \sum_{i=1}^{N} (\hat{\Phi}_i - \bar{\Phi})^2} \tag{11}$$

While the MG estimator is both consistent and efficient under heterogeneous slopes both in the short and long run, Pesaran et al. (1999) propose the Pooled Mean Group (PMG) estimator for increased efficiency when the long-run relationship is slope homogeneous. In the case of natural gas demand in Europe, such common long-run effects could come from similarities in technologies, demographic structure or budget constraints. For our panel ECM in Eq. 8, this means imposing the restrictions

$$\eta_{1i} = \eta_{1j} \wedge \eta_{2i} = \eta_{2j} \wedge \eta_{3i} = \eta_{3j} \quad \forall \quad i, j = 1, 2, ..., N \tag{12}$$

while still allowing heterogeneity in the short-run coefficients and the error variances as with the MG method.

In the case where all predictor slopes are assumed homogeneous, the Dynamic Fixed Effects (DFE) estimator will further offset efficiency losses while remaining consistent (Pesaran et al., 1999). This means also adding cross-sectional equality restrictions to the short-run coefficients $\phi_{li}, \theta_{1li}, \theta_{2li}, \theta_{3li}$ in addition to the PMG long-run restrictions in Eq. 12. The only heterogeneous parameters left in DFE are then the intercepts ω_i and speeds of adjustment ρ_i. Although equal response to changes in the explanatory variables for all countries is a delicate assumption, the pooling effect would present a valuable efficiency benefit for the modest sample size at hand.

4.4 The Hausman specification test

The homogeneity assumptions described above can be tested with a Hausman-style specification test. In EViews (IHS Global Inc., 2022), this is done by first estimating a PMG model with equivalent MG and DFE specifications. Then, for each pair of estimators, the difference in the long-run estimates enters the test statistic

$$\mathcal{H} = (\hat{\beta_1} - \hat{\beta_2})'(\hat{\mathbf{\Sigma_1}} - \hat{\mathbf{\Sigma_2}})^{-1})(\hat{\beta_1} - \hat{\beta_2}) \tag{13}$$

where $\hat{\beta_1} - \hat{\beta_2}$ is a vector of long-run coefficient differences and $\hat{\mathbf{\Sigma_1}} - \hat{\mathbf{\Sigma_2}}$ is the difference of the covariance matrices. Under the null hypothesis of both estimators being consistent and the most homogeneous one being efficient, $\mathcal{H}$ is $\chi^2(k)$-distributed with k as the number of parameters. If the H_0 is rejected, we conclude that the homogeneous estimator is inconsistent.

5 Results

We implement the econometric strategy in R, using the ARDL-package of Natsiopoulos and Tzeremes (2022) and the plm-package for panel data analysis developed by Croissant et al. (2022). The code is retrievable from GitHub[3].

5.1 Results of panel unit root tests

Table 3: Panel unit root tests

	Intercept			Trend		
Variable	Maddala Wu	Levin & Lin	IPS	Maddala Wu	Levin & Lin	IPS
Demand	74.1 ***	-4.4 ***	-3.807 ***	125.7 ***	-5.917 ***	-6.619 ***
Price	24.03	-2.525 ***	-0.247	10.74	0.8414	3.737
Income	56.28 ***	-5.001 ***	-3.32 ***	22.86	-2.112 **	1.374
Weather	186.4 ***	-10.56 ***	-9.929 ***	264.8 ***	-12.55 ***	-13.04 ***
ΔDemand	458.6 ***	-90.33 ***	-42.99 ***	491.3 ***	-79.91 ***	-44.97 ***
ΔPrice	230.6 ***	-109.8 ***	-41.49 ***	218.5 ***	-104.9 ***	-43.94 ***
ΔIncome	64.98 ***	-419.7 ***	-127.9 ***	57.64 ***	-394.8 ***	-135 ***
ΔWeather	700.6 ***	-97.49 ***	-53.86 ***	663.8 ***	-83.82 ***	-52.41 ***

Alternative hypothesis: Stationarity. Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *

Table 3 presents the results of the selected panel unit root tests. All tests reject the null hypothesis that demand contains a unit root. Both the Maddala Wu and the IPS test fail to reject the null hypothesis that price contains unit roots, but all reject the null against the alternative that price is stationary in its first difference. The tests indicate that the weather variable, as expected, is stationary in levels. For income, the tests show no clear conclusion.

Our results indicate that an ARDL bounds testing procedure might be appropriate. The data seem to require a method that can handle both stationary and non-stationary variables. Given our mixed results for demand and income in levels, we can exploit the fact that the ARDL approach does not require the exact order of integration of the variables to be known in advance, and is appropriate when dealing with a mixture of $I(1)$ and $I(0)$ variables (Pesaran et al., 2001). It is also robust to small sample sizes (Nkoro & Uko, 2016). Crucially, a requirement of ARDL modelling is that no variable is integrated of order $I(2)$. Our results in Table 3 indicate that this prerequisite holds, as the null hypothesis of non-stationarity is rejected for the first differences of all variables.

[3]The R-code including the data needed to reproduce our results can be downloaded here: https://github.com/johannov/project_thesis_delivery. The repository also includes the EViews files necessary to estimate a PMG model and perform the Hausman test.

5.2 Specification test results

As there is no available libraries in R for the pooled mean group estimator, we perform the Hausman specification test in EViews on a PMG-specification with lag structure based on the Akaike information criterion (AIC).

Table 4 shows the results from the Hausman tests. We reject the null that PMG and MG are statistically similar, suggesting that MG is the appropriate estimator. We also reject the null of similarity between PMG and DFE estimates[4]. We move on to estimate heterogeneous coefficients both in the short- and long run with the MG estimator.

Table 4: PMG Hausman Specification Test.

Estimator	Test stat.	P-value
Mean Group	15.72	0.0013
Dynamic Fixed Effects	19.33	0.0002

[5]Null hypothesis: Estimator is statistically similar to the PMG estimator.

5.3 Country-specific ARDL results

Results from the bounds testing procedure are shown in Table 5. Using the critical bounds for small sample sizes reported by Narayan (2005), all countries are above the upper bound. Hence, we reject the null hypothesis that no cointegrating relationship exists in favor of the alternative hypothesis that there is one cointegrating vector.

The country-specific estimates used in the mean group estimation are reported in the appendix. The optimal lag order is allowed to vary between countries, selected by the AIC.

The error correction term in table Table 10 is negative and significant at a 1% level for all countries but Poland, indicating that there is a significant long-run relationship between the exogenous variables and demand. The EC-coefficient for Poland has a significance marginally below the 10% level, and we choose to include it in the mean group as the remaining diagnostics show no sign of misspecification. The estimate of difference in weather, indexing low temperatures, is positive and significant for all countries. In the long run, all significant country-specific estimates of price elasticity are negative.

[4]When PMG is inconsistent to MG, this result is expected form the theory but irrelevant for model selection.

Table 5: Bounds test

Country.	Model order	Obs.	F-statistic	Lower bound	Upper bound
AUT	(2,3,3,2)	42	8.614	2.933	4.020
CZE	(2,1,1,2)	35	16.080	3.393	4.410
DEU	(1,0,0,1)	30	7.729	4.290	5.080
DNK	(1,3,2,2)	37	65.000	2.933	4.020
ESP	(2,1,0,1)	34	13.420	3.393	4.410
FRA	(1,2,1,0)	42	37.714	3.373	4.377
HUN	(1,0,1,1)	30	12.170	4.290	5.080
IRL	(1,1,0,1)	35	39.610	4.225	5.050
ITA	(2,3,3,1)	38	7.490	2.933	4.020
LUX	(1,1,1,0)	42	18.960	4.235	5.000
NLD	(1,1,0,2)	42	5.187	3.373	4.377
POL	(2,1,3,3)	36	5.470	2.958	4.100
SVK	(1,1,0,1)	30	8.743	4.290	5.080

Critical values for the upper and lower bound as reported by Narayan (2005) on a 10% significance level. The critical value for each country is based on the maximum number of lags, and the number of observations rounded to the nearest five.

5.4 Residual diagnostics

The residual diagnostics are reported in Table 6. For each country, we conduct the Jarque–Bera test to evaluate whether the residuals are normally distributed. We fail to reject the null hypothesis of normally distributed residuals, for all countries but Italy. In the residuals, we find outliers in 1990 and 1991, where we fail to find plausible explanations such as one-time events or changes in reporting. We consider that by including dummy variables for these observations, we would artificially improve our residuals, without necessarily improving the model fit. In addition, Brooks (2014, p. 210) claims that "for sample sizes that are sufficiently large, violation of the normality assumption is virtually inconsequential". Hogg et al. (2015) suggests that a sample size of 25-30 is "sufficiently large" as a rule as a rule of thumb. As a result, we consider the estimates for Italy to be valid for hypothesis testing.

We perform Ljung-Box tests for autocorrelation in the residuals. We fail to reject the null hypothesis of no autocorrelation between residuals for all countries at all conventional significance levels. We test for heteroskedasticity with the Breusch-Pagan test, and fail to reject the null hypothesis of homoskedasticity for all countries.

Table 6: Residual diagnostics

	Jarque-Bera		Ljung-Box		Breusch-Pagan	
Country	Test-statistic	P-value	Test statistic	P-value	Test statistic	P-value
AUT	3.986	0.136	0.052	0.820	13.848	0.385
CZE	0.427	0.808	0.081	0.776	4.319	0.889
DEU	0.741	0.690	2.440	0.118	6.966	0.223
DNK	0.721	0.697	1.002	0.317	7.261	0.778
ESP	2.394	0.302	0.008	0.930	10.461	0.164
FRA	0.779	0.678	0.887	0.346	8.898	0.351
HUN	0.385	0.825	0.656	0.418	2.905	0.821
IRL	1.435	0.488	0.284	0.594	4.218	0.647
ITA	25.548	0.000	0.558	0.455	13.798	0.314
LUX	2.889	0.236	0.011	0.918	3.942	0.786
NLD	2.439	0.295	0.877	0.349	4.401	0.733
POL	1.588	0.452	1.535	0.215	13.102	0.362
SVK	0.674	0.714	0.478	0.489	5.108	0.530

5.5 Mean group results

Through the MG estimator we obtain an Europe-wide model for natural gas demand. The error correction term, interpreted as the speed of adjustment is estimated to -0.352 and is significant at a 1% level.

The short-run multipliers, reported in Table 8 capture the contemporaneous impact of a shock to the explanatory variables on natural gas demand. Weather is the only variable that is found to have a significant short-run impact of 1.789. The short-run price elasticity is -0.116 and short-run income elasticity 0.280. Neither price nor income have significant impact in the short run at any conventional level.

In the long-run, we report a price elasticity of demand of -0.399, significant at a 1% level. The estimated income elasticity is 0.892, and the long-run impact of price 0.489. We find that the weather effect is for the most part apparent in the short run, with a greater magnitude and level of significance than in the long run.

Table 7: Mean group coefficient results

Variable	Intercept	$\Delta D_{(-1)}$	ΔP	$\Delta P_{(-1)}$	$\Delta P_{(-2)}$	ΔY	$\Delta Y_{(-1)}$	$\Delta Y_{(-2)}$	ΔW	$\Delta W_{(-1)}$	$\Delta W_{(-2)}$	ECT
Mean	-3.256*	-0.014	-0.041	0.018	-0.011	0.100	0.019	-0.019	0.631***	0.017	-0.016	-0.352***
	(1.809)	(0.035)	(0.034)	(0.020)	(0.036)	(0.072)	(0.090)	(0.095)	(0.100)	(0.052)	(0.016)	(0.062)

D: demand of natural gas, P: price of natural gas, Y: income, W: weather in heating degree days.
Standard error reported in parenthesis. Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *

Table 8: Mean group elasticity results

Short run			Long run		
P	Y	W	P	Y	W
-0.116	0.283	1.789***	-0.399***	0.892**	0.489*
(0.077)	(0.205)	(0.204)	(0.102)	(0.321)	(0.266)

D: demand of natural gas, P: price of natural gas, Y: income, W: weather in heating degree days.
Standard error reported in parenthesis. Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *

6 Discussion

6.1 The absence of a short run price response

The impact of the weather variable, representing the temperature-driven need for heating, is estimated to 1.789, and is the only variable that is found to be significant in explaining short run changes in natural gas demand. The interpretation of this is that 1% increase in heating degree days from one year to another is associated with a 1.789% contemporaneous increase in natural gas demand. Heating and cooling accounts for half of the EU energy consumption, almost half of it fueled by natural gas European Commission (n.d.). With this in mind, it is reasonable that cold weather has a strong effect on residential demand.

We find no significant short-run impact of natural gas price on demand, indicating that households do not immediately respond to price changes. Bernstein and Madlener (2011) also fail to find a significant short-run price elasticity for almost half of the countries, but still report a mean estimate of -0.24. Asche et al. (2012) also report several insignificant results on a country-level using annual data. Auffhammer and Rubin (2018) estimate a short-run elasticity of demand of -0.23 to -0.17, Alberini et al. (2020) an elasticity of -0.16 and Dagher (2012) an elasticity of -0.091. These are all studies on monthly aggregated data, sampling at the same frequencies as the price changes reaches the consumer. Studies with monthly observations might be more appropriate to capture short-run consumer responses than annually data, yielding significant results. The meta-analysis of (Labandeira et al., 2017) finds a mean short-run elasticity of -0.180 across natural gas studies.

Our results indicate that households do not show a strong response to short-run price changes. Deryugina et al. (2020) explain this finding when evaluating the dynamics of energy demand and state that "when consumption depends on goods that are durable or habit-forming, consumers may take years to respond fully to a price change".

This is not surprising, as information on price and consumption often is either inaccessible or presumed irrelevant to the consumer. Deryugina et al. (2020) argue that for end-users, the benefit of tracking price changes might be small relative to the cost of paying attention. Alberini et al. (2020) also address this issue of prices not being salient to the consumer. Without sufficient information of the price fluctuations, they can not change their consumption behavior accordingly. In the absence of modern metering devices, consumers still read off their natural gas meters and report their consumption infrequently, limiting their ability to adjust their consumption in real-time. If consumers are to effectively respond to short-run price changes and stabilize the natural gas market during periods of restricted supply, they must have access to information on both their consumption and prices at a higher frequency.

6.2 Our long-run results in context of existing literature

We report a estimate of long-run price elasticity of demand of -0.399, which implies that natural gas demand is inelastic to price in the long-run. However, with a high level of significance on the mean estimate and negative sign for all significant long-run price elasticities at country level, we are confident that such an adjustment exists.

As discussed in the literature review, the econometric methods vary greatly across studies, as well as the interpretation of price elasticity of demand, especially in the long-run. As a result, the estimates for price elasticity of demand from different studies are not directly comparable, but could indicate if our results are reasonable in magnitude. Our estimate of long-run price elasticity of demand is similar to that of Liu (2004) of -0.365, and falls within the range of that of Asche et al. (2012) of -0.6 to 0. However, our estimate is lower than that obtained by Bernstein and Madlener (2011) of -0.51, despite using a similar econometric approach, as well as the results of Alberini et al. (2011) of -0.647. The mean found by the meta analysis of Labandeira et al. (2017) is -0.684, which is also higher than our results. Our estimate is lower than that of Dagher (2012) of -0.235. Overall, our estimates seems to be within the lower range of previous studies.

Our analysis reveals a long-run income elasticity of 0.892. This means that a 1% increase in income would lead to a near proportional increase in natural gas demand. The relationship between energy consumption and economic growth has been extensively studied in the Energy-Growth Nexus literature, which examines the interplay between economic development and energy use[6]. We recognize the need for more sophisticated methods to draw conclusions about the causal effects of income on natural gas demand.

The speed of adjustment is estimated to -0.352, indicating that a near-complete adjustment of 95% would take 7 years. Household investments in infrastructure and durables for natural gas end-use are expensive and have a long lifetime, which might explain why households take time to adjust their consumption (Asche et al., 2012),

[6]For an introduction to this field of literature, we recommend reading Hajko et al. (2018)

(Deryugina et al., 2020). In combination with the non-significant short-run response of price, this should concern policy makers hoping for price to dampen the demand from households during events of tight natural gas supply.

The limitation of data availability should be kept in mind when evaluating our results. First, more observations could help provide more reliable country-specific estimates. Second, we have assumed constant elasticities. To examine time-varying coefficients or other structural changes, more frequent observations or a larger cross-section would be needed. Our model is estimated on annual observations from 1979 to 2020, a period with large changes in the natural gas market, both due to infrastructure expansion and geopolitical events. The need for an European benchmark for price elasticity based on a more recent time period for use in policy and research is still needed. We encourage researchers and statistical offices to collect more frequent observations of natural gas prices and residential consumption for a wider range of countries.

6.3 Evaluating the MG estimator

We present the country-specific estimates for the reader's insight, but caution that these estimates may not be reliable due to the limited amount of data available. With at most 42 observations per country, the estimates may not accurately capture the true relationship between the variables and may be influenced by one-off events. On the other hand, by ignoring the heterogeneity, a homogeneous model will fail to account for structural differences between countries, leading to high bias.

By averaging the separately estimated models through the MG estimator, we can reduce the variance of the estimates and provide a more robust Europe-wide estimate of the price elasticity of demand, which is the main result of this report. By balancing this bias-variance trade-off, we can draw more reliable conclusions.

Even though the results from the MG estimator have considerably lower variance than the country-specific estimates, Pesaran et al. (1999) find in their empirical application that the PMG estimator provides superior efficiency in estimating the long-run parameters. This would particularly benefit our long-run income and weather estimates, which have higher standard errors than price. However, since the homogeneity assumption needed to employ PMG does not hold for this data set, the variance must be carefully regarded as part of the result.

When estimating the mean, there are obvious alternatives to the simple weights of Pesaran and Smith (1995) used in this paper. Hsiao et al. (1999) evaluate the

Bayes-estimator, giving more weight to individual coefficient estimates with low variance, but only consider short-run coefficients. Because of the variance-dependent weights, the estimate would also be less robust towards extreme values than the simple MG. In a recent paper, Lee and Sul (2022) try to balance the trade offs between efficiency gains and robustness by "trimming" weights for both high and low variances. However, the panels discussed in both studies are substantially wider than ours, suggesting that more countries should be included before more sophisticated weights can be used successfully.

Although pointed possible by Pesaran and Smith (1995), an empirical application allowing heterogeneous lag structure within the MG has not been done before in the econometric literature, to our best knowledge. This may very well originate from lacking software to provide such estimates with consistent standard errors and t-statistics. To approximate these, well-established statistical methods from the ARDL-package (Natsiopoulos & Tzeremes, 2022) was replicated in a custom script on the mean of the group-specific coefficients using their calculated variance-covariance matrices for the means. This method gives comparable results with existing software (with more restrictive assumptions about the lag structure), but should be verified further with bootstrapping and simulation.

7 Conclusion

In this paper, we have used the mean group estimator with the autoregressive distributed lag cointegration approach to estimate the elasticities of natural gas demand in the European Union. Our custom implementation of the mean group estimator allows for heterogeneous lag structure in the underlying ARDL specifications, providing a novel contribution to the econometric literature. The ARDL cointegration approach allows us to address the issue of spurious regression and to use variables with mixed degree of integration, ignored by the majority of the previous studies.

Our results show an inelastic long-run price elasticity of demand of -0.399 and a long-run income elasticity of 0.892. In the short run, only weather has a significant impact with an elasticity of 1.789. These findings have important implications for policy makers and gas market modellers - including paying more attention to the weather report than prices when planning for short-run security of supply.

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Appendix

Table 9: ECM long-run coefficients per country

Country	Intercept	P	I	W
AUT	-27.295***	-0.205***	2.303***	1.334***
	(3.777)	(0.039)	(0.152)	(0.305)
CZE	14.225	-0.361	-0.237	-0.319
	(9.728)	(0.217)	(0.452)	(0.761)
DEU	-19.829*	-0.639***	2.098***	1.133
	(10.988)	(0.232)	(0.635)	(0.724)
DNK	13.508*	-0.184	-1.204**	0.909*
	(7.56)	(0.23)	(0.549)	(0.458)
ESP	-26.664***	-0.033	3.157***	0.152
	(8.502)	(0.33)	(0.517)	(0.725)
FRA	-9.686***	-0.468***	1.042***	1.018***
	(1.946)	(0.067)	(0.168)	(0.143)
HUN	22.709	-0.712**	0.119	-1.308
	(17.235)	(0.323)	(0.382)	(1.323)
IRL	19.111	-0.965***	0.426	-1.518
	(13.61)	(0.24)	(0.436)	(1.339)
ITA	-14.307**	0.259	0.875***	1.278**
	(5.789)	(0.307)	(0.194)	(0.565)
LUX	-12.678***	-0.02	0.925***	1.162***
	(3.601)	(0.079)	(0.164)	(0.334)
NLD	3.211	-0.479***	0.02	0.754
	(5.435)	(0.1)	(0.233)	(0.452)
POL	-8.226	-0.379	0.763*	0.976
	(8.729)	(0.256)	(0.417)	(0.804)
SVK	-6.337	-0.994**	1.308*	0.785
	(11.11)	(0.444)	(0.668)	(1.08)

Table 10: ECM short-run coefficients per country

Country	Intercept	$\Delta D_{(-1)}$	ΔP	$\Delta P_{(-1)}$	$\Delta P_{(-2)}$	ΔY	$\Delta Y_{(-1)}$	$\Delta Y_{(-2)}$	ΔW	$\Delta W_{(-1)}$	$\Delta W_{(-2)}$	ECT
AUT	-19.662***	0.207	-0.069	0.108	0.213**	0.704*	-0.881	0.637	1.004***	-0.316*	-	-0.720***
(2,3,3,2)	(4.709)	(0.124)	(0.080)	(0.074)	(0.078)	(0.347)	(0.551)	(0.514)	(0.135)	(0.166)		(0.129)
CZE	3.285	-0.289*	0.176*	-	-	0.371	-	-	0.949***	0.551***	-	-0.231***
(2,1,1,2)	(1.933)	(0.161)	(0.100)			(0.239)			(0.096)	(0.173)		(0.045)
DEU	-2.811	-	-	-	-	-	-	-	0.773***	-	-	-0.142***
(1,0,0,1)	(1.897)								(0.074)			(0.040)
DNK	2.239*	-	0.069	-0.057	0.032	-0.238	0.592***	-	0.682***	0.074	-	-0.166***
(1,3,2,2,)	(1.154)		(0.047)	(0.051)	(0.050)	(0.215)	(0.204)		(0.053)	(0.052)		(0.022)
ESP	-7.142**	-0.239	-0.268	-	-	-	-	-	0.265*	-	-	-0.268***
(2,1,0,1)	(3.063)	(0.145)	(0.173)						(0.130)			(0.046)
FRA	-7.493***	-	-0.173	0.222*	-	0.162	-	-	-	-	-	-0.774***
(1,2,1,0)	(1.660)		(0.115)	(0.111)		(0.454)						(0.075)
HUN	3.445*	-	-	-	-	0.380**	-	-	0.574***	-	-	-0.152***
(1,0,1,1)	(1.754)					(0.170)			(0.106)			(0.053)
IRL	3.523	-	0.065	-	-	-	-	-	1.021***	-	-	-0.184***
(1,1,0,1)	(2.165)		(0.095)						(0.182)			(0.033)
ITA	-6.140**	0.083	-0.180	-0.035	-0.392***	-0.136	0.207	-0.998**	0.971***	-	-	-0.429***
(2,3,3,1)	(2.234)	(0.133)	(0.137)	(0.113)	(0.118)	(0.326)	(0.47)	(0.472)	(0.161)			(0.121)
LUX	-7.013***	-	-0.114*	-	-	-0.129	-	-	-	-	-	-0.553***
(1,1,1,0)	(1.596)		(0.064)			(0.384)						(0.096)
NLD	0.845	-	0.038	-	-	-	-	-	0.900***	0.058	-	-0.263***
(1,1,0,2)	(1.337)		(0.066)						(0.069)	(0.063)		(0.077)
POL	-4.229	0.059	-0.059	-	-	0.182	0.330	0.109(0.6)	0.587**	-0.140	-0.207	-0.514
(2,1,3,3)	(2.656)	(0.214)	(0.102)			(0.372)	(0.400)		(0.225)	(0.161)	(0.122)	(0.299)
SVK	-1.176	-	-0.016	-	-	-	-	-	0.473***	-	-	-0.186**
(1,1,0,1)	(2.064)		(0.116)						(0.161)			(0.076)

D: demand of natural gas, P: price of natural gas, Y: income, W: weather in heating degree days.
Standard error reported in parenthesis. Significance levels: 0-0.01: ***, 0.01-0.05: **, 0.05-0.1: *