



And yet it moves: A study of natural gas consumption in Italy at the turn of the 2022 energy crisis[☆]

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ABSTRACT

This paper presents the first econometric analysis of Italian residential natural gas consumption at the turn of the 2022 energy crisis. Using daily data from 2012 to 2025 and applying the Autoregressive Distributed Lag (ARDL) and Error Correction Model (ECM) methodologies, we investigate how the unprecedented price shocks following Russia's invasion of Ukraine affected Italian households' consumption patterns. Our analysis demonstrates that the crisis triggered a persistent transformation in consumers' behavior that extends beyond the immediate crisis period. Before December 2021, natural gas demand was essentially price-inelastic. However, the energy crisis altered this relationship, with price elasticity increasing from virtually zero to 0.34 by 2023 — a transformation that persists even as prices have moderated. The elasticity is even larger (up to 1.90) when we refer to the price-responsive component of demand. Moreover, the decomposition of total demand into heating and baseload components reveals that space heating demand served as the primary adjustment mechanism during the crisis. We estimate approximately 11.9 billion cubic meters in savings between 2022 and 2025, translating to 13 billion euros in financial savings. Finally, we find evidence that the lockdowns during the Covid-19 pandemic and the policy measures introduced in 2022–2023 to incentivize gas savings had a limited effect on gas consumption.

1. Introduction

Natural gas is one of the most important energy sources for Italy, where in 2022 it accounted for 44% of total power generation and 69% of gross thermoelectric generation (Terna, 2022). The Russian Federation has historically been Italy's single largest natural gas supplier, accounting, on average, for over 43% of total yearly imports between 2012 and 2021. However, Russia's role in the Italian energy policy drastically changed after the Russian invasion of Ukraine in February 2022 and the subsequent energy crisis. In particular, Italy reduced its imports from Russia from 28 billion m³ in 2021 to 5.5 billion m³ in

2024, compensating for this contraction with increased imports from Algeria and LNG.

Following the contraction in Russian natural gas supply in 2022 and the associated price spikes, the Italian government took action to foster gas savings by capping thermostat settings and shortening the heating season. Unprecedented price increases hit households' budgets, with subsidies available only to low-income consumers. These policies, combined with virtuous individual behavior and an unusually warm autumn and winter, led to a significant reduction in gas consumption, allowing Italy to navigate the cold season of 2022–2023 without completely depleting its gas storage.

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The overlap of several factors affecting gas consumption, in turn, makes it challenging to identify the distinct effects and, in particular, the reactivity of consumers to the unprecedentedly high prices. Early analysis and commentary – e.g., [IEA \(2023\)](#) – simply compared the total volumes of natural gas consumed in 2022 and 2021. These experienced a decrease – for example, in Italy, total imports decreased by 4.18%, whereas imports from Russia fell by 59.33%, more than halving in a single year – but the timing of the reduction in natural gas consumption and the extent to which it was caused by the mild weather conditions or by consumers' reaction to high prices remain unclear.

Recent papers, such as [Ruhnau et al. \(2023\)](#), [Kächele and Grothe \(2023\)](#) and [Jamiissen et al. \(2024\)](#), focus mainly on the German case, and no comprehensive study exists on Italian consumers' response to the energy crisis, despite Italy's role as the second-largest importer of Russian natural gas before the conflict. Therefore, this paper presents an empirical investigation aimed at:

1. modeling the long-run fundamentals determining households' natural gas demand in Italy;
2. assessing consumers' response (if any) to the 2022 energy crisis and its persistence over time;
3. estimating potential gas savings from an adaptation in consumption patterns and highlighting their financial relevance.

We develop our empirical analysis by constructing a database of daily consumption by Italian households and small commercial activities. Then, we adopt the Autoregressive Distributed Lag (ARDL) and Error Correction Model (ECM) methodologies with a linear specification of households' natural gas demand, which is common in the literature. Our main controls are measures of weather conditions and an index of the retail price.

Our analysis shows that the 2022 energy crisis fundamentally altered Italian residential natural gas consumption, with a permanent break in consumption patterns from mid-2021 onward. The analysis reveals that, pre-crisis, consumption did not react to the (moderate) price changes, and was driven only by weather conditions. After mid-2021, price elasticity gradually increased from virtually zero to 0.34 over the years 2021–2024, with a reduced reaction of consumption to severe weather conditions. The estimated elasticity is even larger (up to 1.90) if computed with respect to the price-responsive component of demand by netting out the effects of the other factors. Space heating demand served as the primary adjustment mechanism. We test whether the lockdowns during the Covid-19 pandemic and the policy measures to foster gas savings affected gas consumption, finding no or a limited impact. Remarkably, these behavioral changes persist even as prices have normalized, suggesting a permanent shift in consumption patterns that may stem from changes in consumption habits and from investment in energy-efficient devices. The change in consumption patterns allowed households to save approximately 11.9 billion cubic meters, worth approximately 13 billion euros, between 2022 and 2025.

The paper is organized as follows. Section 2 highlights how our paper contributes to the literature; Section 3 describes the data and the methodology followed to construct them; Section 4 describes the econometric model and the methodology adopted (ARDL and ECM). We then move to the results of the estimates of the econometric model and of yearly elasticities in Section 5, presenting a breakdown of total demand between baseload and heating in Section 6; Section 7 translates our results into quantity and monetary savings from the change in consumption behavior during the energy crisis. Several robustness checks and extensions are presented in Section 8. Finally, Section 9 draws some conclusions.

2. Contribution to the literature

As pointed out by [Jamiissen et al. \(2024\)](#), the existing literature on the price elasticity of natural gas demand is rather limited. Many contributions date back to the pre-crisis phase, when the market was

relatively stable, and price variations were small compared with the high instability of recent years. These empirical studies have mainly focused on estimating average or long-run elasticities, with some variability in the results, and a prevailing aggregation at the country level and yearly frequency. The empirical evidence found in these studies consistently shows that natural gas consumption is inelastic. [Dong et al. \(2019\)](#) and [Erias and Iglesias \(2022\)](#) provide two excellent and comprehensive reviews of the available studies on the price elasticity of natural gas and of their estimates.

Focusing on European countries, [Dilaver et al. \(2014\)](#) uses annual country-level data over 1978–2011 to estimate a long-run price elasticity of -0.16 in OECD Europe. [Asche et al. \(2012\)](#) rely on residential sector's annual data over 1978–2002 from twelve European countries (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Spain, Switzerland, and the UK) to estimate long-run own-price elasticities between -0.60 and 0 . [Bernstein and Madlener \(2011\)](#) employ an Autoregressive Distributed Lag (ARDL) model with annual data on residential demand of twelve OECD countries over 1980–2008 to estimate a long-run own-price elasticity of -0.51 , while [Berkhout et al. \(2004\)](#) estimate a price elasticity of natural gas demand of the residential sector of -0.2 for the Netherlands in 1996. Finally, the meta-analysis of [Labandeira et al. \(2017\)](#) finds an average long-run price elasticity of natural gas demand equal to -0.568 .

Some more recent papers have focused on households' consumption of natural gas during the 2022–2023 energy crisis, and the unprecedented price spikes and gas flow redirections. Looking at the German market, the single largest importer of Russian natural gas before the energy crisis, [Ruhnau et al. \(2023\)](#) builds on previous research by [Ruhnau et al. \(2019\)](#) and [Ruhnau and Muesel \(2022\)](#). Controlling for weather patterns, they estimate a reduction in consumption of 10% in March 2022 and a maximum reduction of 28% in September 2022 for German households. [Kächele and Grothe \(2023\)](#) instead estimates savings in 2022 amounting to 10.3% of previous years' consumption, a volume of natural gas equivalent to 37 TWh, or the yearly consumption of circa 3.3 million households. [Olmez Turan et al. \(2025\)](#) provide a large-scale panel analysis of natural gas demand across 23 EU countries over 2011–2022, employing a LASSO-IV approach to select instruments from a wide set of weather shocks. Their panel estimate is -0.80 , but country-level estimates display substantial heterogeneity, with a cross-country median of -0.13 . For Italy specifically, they obtain an elasticity estimate of -0.09 , consistent with a largely inelastic domestic demand.

The study closest to ours in its Italian focus is [Favero and Grossi \(2023\)](#), which, to the best of our knowledge, is the most credible existing micro-level analysis of natural gas demand in Italy. Using monthly billing data for over 51,000 residential and non-residential consumers in the Veneto region over 2016–2018, the authors estimate a preferred household price elasticity of -0.52 to -0.55 , instrumented with ARERA baseline prices, with the full household range spanning -0.35 to -0.83 across specifications. However, their analysis is confined to a single Italian region, to a short pre-crisis window, and yields only a single point estimate leaving open the question of how household responses may have evolved during the unprecedented price spikes of 2022–2023.

Our paper contributes to this literature on several grounds. First, we develop the first detailed high-frequency analysis of the Italian market, the second-largest European gas-consuming area after Germany. Secondly, our modeling of gas demand enables us to obtain time-varying estimates of elasticities that capture households' adaptation to unprecedented price spikes. Third, extending the analysis beyond the 2022–2023 period, we find some evidence of a structural change in household behavior once back to less extreme market conditions. Moreover, we separately analyze the consumption due to space heating and baseload uses, identifying in the former component the term that has driven the adjustment in household demand. Finally, we perform several extensions to test the robustness of the results, including the potential impact of lockdowns during the Covid-19 pandemic and the

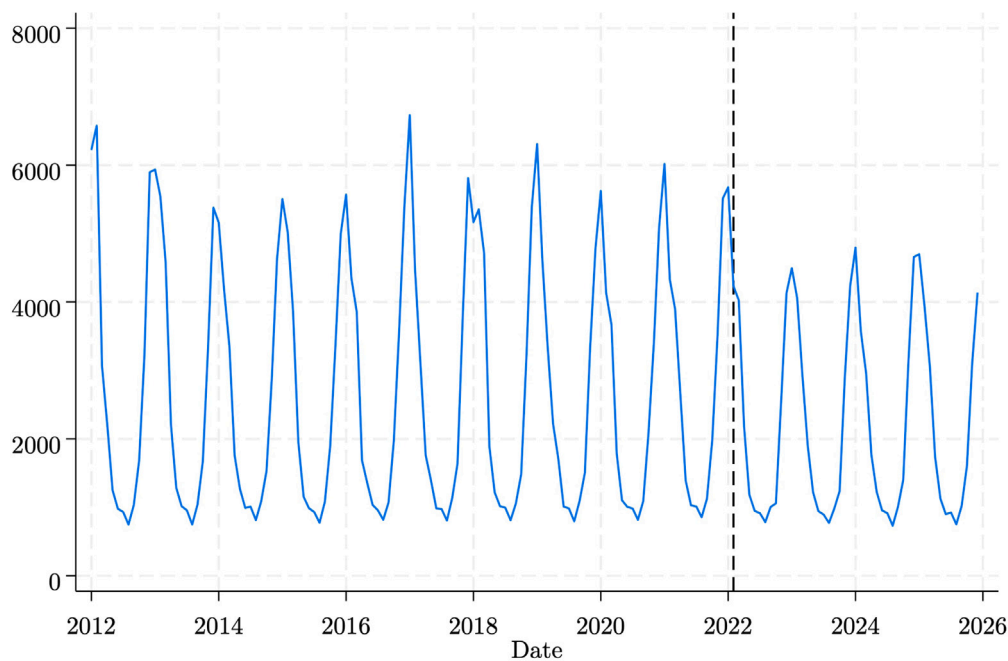


Fig. 1. Monthly time series of distribution network's natural gas consumption (millions of Sm³).
 Note: The vertical line marks February 2022 and the Russian invasion of Ukraine.

specific effects of some temporary policy measures introduced by the Italian Government to foster gas savings.

Our methodology is similar to that in Jamissen et al. (2024). The authors employ an ARDL model at daily resolution to estimate the price elasticity of natural gas demand among German small consumers during the 2018–2023 period, controlling for the weather-dependency of gas consumption. They estimate the long-run price elasticities of natural gas to be -0.01 for wholesale prices and -0.04 for retail prices, indicating highly inelastic demand that requires large price changes to trigger short-term adjustments. Compared with their result, our paper allows us to measure the average elasticity year by year rather than only the average elasticity over the entire period, thereby better capturing adjustments in households' consumption patterns.

3. Data sources and methodology

In this Section we describe in detail the data sources and the methodology adopted to construct the variables of the econometric model. Although all variables except the price index are at daily frequency, in the figures we represent monthly averages and/or sums to ease capturing the underlying tendencies out of the daily variability.

3.1. Natural gas consumption

Data on the daily consumption of natural gas of households, residential buildings, and small commercial activities delivered through the distribution network in Italy is released by Snam S.p.A.,² the Italian network grid operator (Snam, 2025). More precisely, the variable “Reti di Distribuzione” (i.e., “Distribution Networks”) corresponds to the amount of standard cubic meters³ (Sm³) of gas delivered through the distribution network and constitutes our measure of residential sector

natural gas demand. The gas balances at daily resolution are retrieved from January 1st, 2012, to December 31st, 2025. These data constitute the variable gas_t , for which we obtain 5114 daily observations.

Although our methodology could in principle be applied also to smaller territorial units than the entire country, data on gas consumption are available only at the national level, as Snam S.p.A. does not publish geographically disaggregated data. Hence, our analysis has to proceed for the entire Italian territory. However, we can use provincial-level information for many controls and construct weighted averages at the national level.

The variable on gas consumption also includes a component attributable to small commercial activities operating from residential buildings – such as hair salons, bakeries, and restaurants – which cannot be separated from household consumption in the publicly available data. However, we argue that this feature of the data does not bias our analysis significantly. Small commercial activities of this kind rely on natural gas predominantly for space heating rather than for industrial processes – which are captured by a completely different time series published separately by Snam S.p.A. –, and thus display consumption patterns that are not fundamentally different from those of households – in particular, they should display the same strong seasonal dependence on weather conditions that characterizes residential demand. Finally, correspondence with Snam's technical staff confirms that these activities constitute a minor share of total distribution network consumption, so that any distortion they introduce is bounded in magnitude.⁴ In any case, in the last part of the paper we run some robustness checks that enable us to control for some confounding effects of this component. In particular, we include two sets of temporal dummies to control for the periods during which Italy was subject to lockdowns due to the Covid-19 pandemic, when commercial activities were shut down.

² Each balance provides for each day of the month the amount of gas delivered through the distribution network in Italy.

³ Standard Cubic Meter is a unit of volume used primarily for gas measurements. Specifically, it refers to the volume of a gas at a standard temperature and pressure of 15°C (288,15 K) and 1,01325 bar.

⁴ The claims advanced in this paragraph are supported by direct communication between the authors and Snam S.p.A., the sole operator of the Italian natural gas transmission and distribution infrastructure. As a regulated monopolist with full visibility over the composition of distribution network flows, Snam constitutes the primary and most authoritative source on the structure of the variable “Reti di Distribuzione”.

The behavior of the distribution network's consumption (from now on, simply "natural gas consumption" or "consumption") displays a clear seasonal pattern, as it is mostly driven by the demand for space heating. Nevertheless, significant differences can arise from year to year, in particular with respect to the peak consumption during the coldest months of the year (December, January, and February) if the winter season in a given year is relatively mild compared with other years. Fig. 1 plots the values of the variable gas_t , aggregated at the monthly level to smooth inter-day variability.

It is possible to notice the particularly low winter consumption in 2022/2023, 2023/2024, and 2024/2025, which suggests a significant contraction in gas consumption by households, a pattern that has also been observed for total gas consumption. Disentangling the causes of this drastic adjustment, which coincides at the same time with warm winter conditions and unprecedented price spikes, is the main challenge in our empirical exercise.

3.2. HDDs: Heating degree days

Heating degree days are a long-established methodology – e.g., see already (Thom, 1954) – which allows to control for the dependency of natural gas consumption on weather conditions, and specifically on outside temperatures, providing an index of the cumulative daily heat deficit below a reference threshold, which proxies the expected demand for space heating. The variable two-meter temperature is retrieved in daily means from the CDS toolbox of the ERA5-Land database (Muñoz Sabater, 2019) from January 1st, 2012, to December 31st, 2025. Adapting the notation of Kozarcin et al. (2019), the variable heating degree days (HDD_t) is then constructed in six steps.

1. We set a measure of the external temperature of the country-specific heating threshold $T_0 = 15.61^\circ\text{C}$, based on Kozarcin et al. (2019).
2. We define our territorial unit x as a province, and X as the set of the 107 Italian provinces.
3. We retrieve the average daily outside temperature T_t^x for province $x \in X$ and day t from the CDS toolbox of the ERA5-Land database (Muñoz Sabater, 2019) from January 1st, 2012, to December 31st, 2025.⁵
4. We compute, for each cell/province $x \in X$ and day t , the difference, if positive, between the threshold T_0 and the daily average temperature T_t^x according to:

$$HDD_t^x = \begin{cases} T_0 - T_t^x & \text{if } T_0 > T_t^x \\ 0 & \text{if } T_0 \leq T_t^x \end{cases}$$

that is, the variable HDD_t^x records how much a day t in province x has been colder than the threshold.

5. Defining as p_x the population in province x and as p the total Italian population, the population-weighted measure of heating degree days in day t is:

$$HDD_t = \frac{1}{p} \sum_x p_x \cdot HDD_t^x. \quad (1)$$

Hence, the index HDD_t corresponds to a population-weighted average of the daily HDDs of the 107 Italian provincial capitals, capturing the average difference between local temperatures and the threshold in

a given day weighted by all Italian provinces' population. Data on the population is retrieved from the Italian National Institute of Statistics (ISTAT) database on the national population in 2024.

HDDs display a clear seasonal pattern, shown in the right panel of Fig. 2, where monthly averages are displayed.

After a minimum of virtually zero during the warm months between June and September, they begin to increase as temperatures fall down during autumn and winter, reaching then a maximum in the months of December, January, and February, the coldest months of the year, corresponding to the peak in demand for space heating. The left panel shows the entire time series, and highlights significant variations from year to year, especially in the peaks during the winter months. Notice in particular the significantly lower peaks in the winter and fall of 2022/2023, 2023/2024, and 2024/2025, which were characterized by temperatures largely above the long-term averages for the period.

3.3. Surface net solar radiation

The surface net solar radiation complements the HDDs index to capture the relevant impact of weather on gas consumption. The variable surface net solar radiation is retrieved in daily means from the CDS toolbox of the ERA5-Land database (Muñoz Sabater, 2019) from January 1st, 2012, to December 31st, 2025 for each province, following the same geolocalization methodology of the variable HDD_t . A measure of the daily population-weighted surface net solar radiation is then computed.

As shown in Fig. 3, the SNSR displays a seasonal trend which is intuitively opposite to that of heating degree days: the solar radiation is highest during warm months and lowest during wintertime. In fact, the two variables display a strong negative correlation of -0.72 . However, there is also a significant dispersion around the linear relationship between the two variables (see Fig. 4), suggesting that including both measures improves the explanatory power of our estimates.⁶

3.4. Prices

To assess the responsiveness of consumers, we include in our model a measure of prices. Constructing a representative measure of retail prices is challenging due to the high degree of heterogeneity in the final prices of natural gas paid by consumers, which can be traced back to the many different kinds of contracts available in the market. Retailers offer a basket of contracts that may include floating or fixed prices with different indexation mechanisms, in addition to a regulated contract whose price is determined by the regulatory agency for energy markets, ARERA.

To address this issue, we consider the consumer price index *Gas di Città e Gas Naturale* published by the Italian National Institute of Statistics (ISTAT) at monthly resolution (COICOP code 04521). This index is computed starting from the prices of offers published by retail suppliers on the online portal of the regulatory authority ARERA, which includes almost all the available commercial offers, and from the regulated price set by ARERA. From these two sources, separate price indexes are constructed: one for the free market and one for the regulated market. These indexes are then combined using weights related to consumption (ISTAT, 2024). The resulting time series, therefore, constitutes a representative index of the dynamics of the average retail price of natural gas paid by consumers at the national level.

Since the gas bills are received every two months, the latest measure of price that customers observe in their bill is lagged. Moreover, in

⁵ Operationally, we consider a cell with dimension $0.1^\circ \times 0.1^\circ$ centered on the provincial capital of province x as representative of the entire province's weather conditions. When recovering the time series for T_t^x , climate data is unavailable for 18 of the 107 original grid cells. These correspond to Italian provincial capitals on the coast or close to it, whose assigned grid is centered on water or very close to it. To solve this problem, these eighteen cells are replaced with the immediately adjacent inland cell closest to the provincial capital of interest.

⁶ The precision of our estimates and our findings is marginally improved by the inclusion of the solar radiation index, which indeed is significant at any confidence level in our specification, thus proving that multicollinearity is not an issue and that the solar radiation index truly captures a differential effect with respect to HDDs.

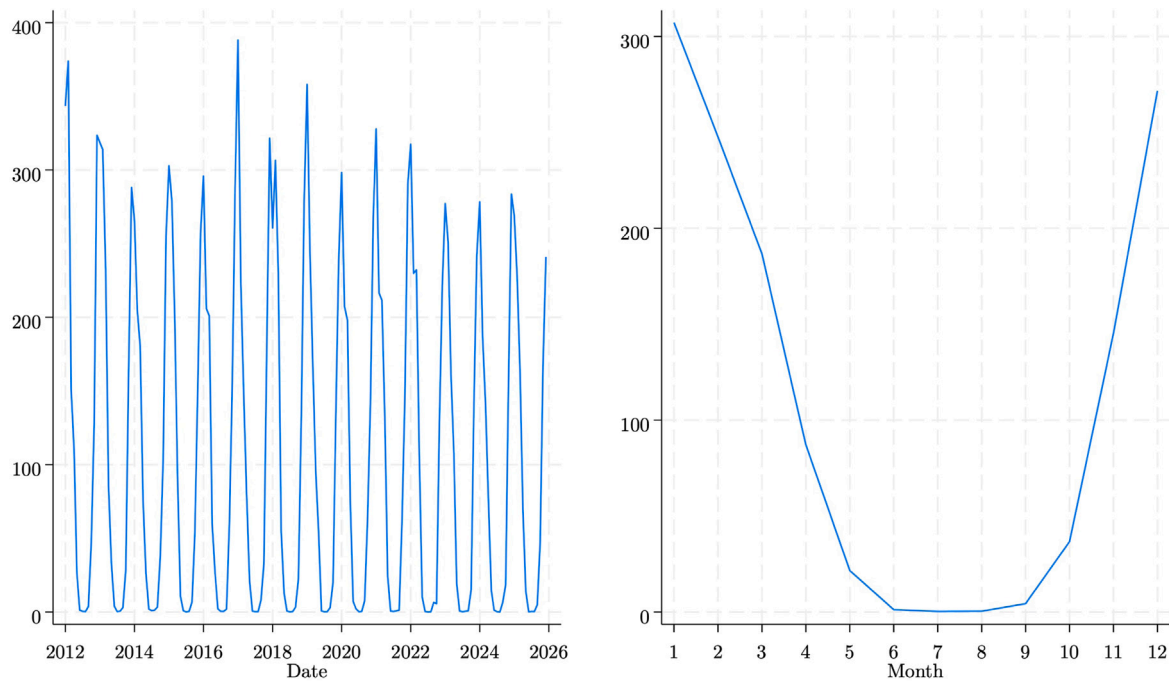


Fig. 2. Monthly and average monthly HDDs time series.

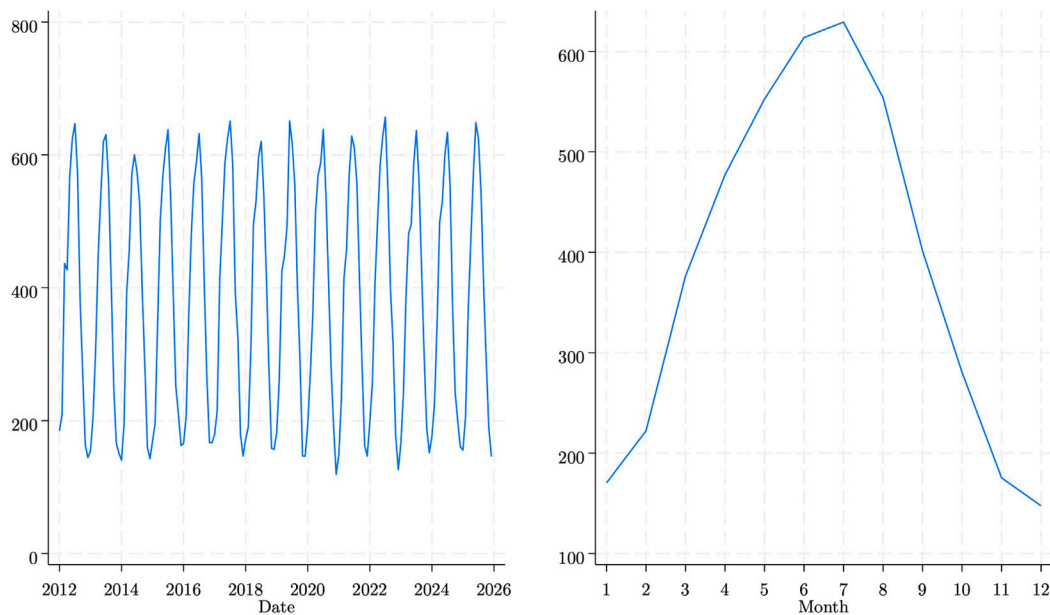


Fig. 3. Monthly and average monthly NSNR time series (millions of J/m^2).

2022 still one third of consumers were under the ARERA's regulated regime for gas consumption rather than in the free market (ARERA, 2023) and the regulated price was updated every three months. Hence, the price index in our analysis is lagged by three months to allow for all consumers to adjust their consumption to the price observed in their bills. Therefore, taking into account the lags in adjustment and delivery of bills, a three-months lag turns out to be an accurate depiction of the consumers' information and reaction. Fig. 5 plots the resulting time series of the three-month lagged price index at monthly resolution.

Notice that the average lagged retail price was relatively stable, with low variability, from 2012 to 2021. It began to increase significantly in the fall term 2021 and, more strongly, in the early months of 2022 with the Russian invasion of Ukraine, reaching its historical maximum

during the summer of 2022. Then it started to decline to an apparently stable, although higher, level by the end of 2023.

4. The econometric model

In this Section we present the econometric models adopted in our analysis.

4.1. The ARDL model

Following the established literature on natural gas consumption, we employ in our analysis an Auto Regressive Distributed Lag (ARDL)

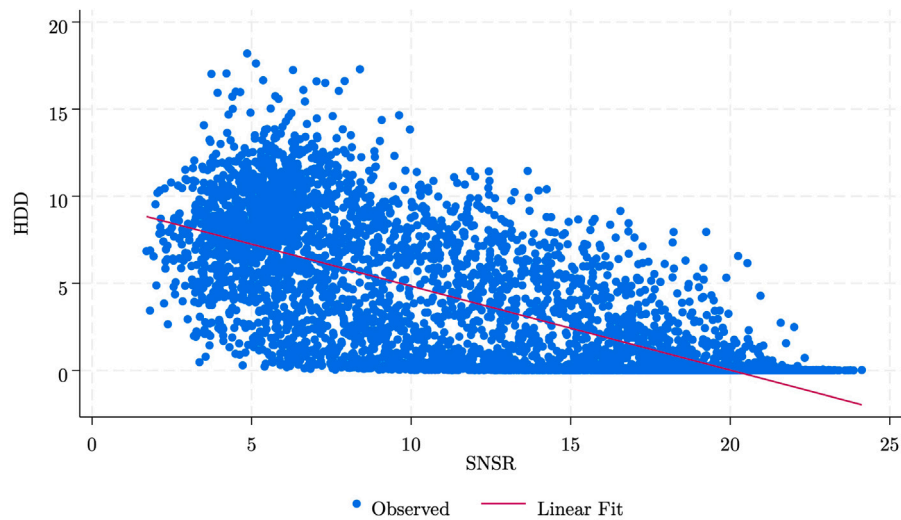


Fig. 4. Daily HDDs and SNSR ($\rho = -0.72$).



Fig. 5. Lagged monthly price index. *Note:* The vertical line marks February 2022 and the Russian invasion of Ukraine.

model.⁷ The ARDL model is well-versed at dealing with non-stationarity, an issue that arises in our model, where the price index variable is indeed non-stationary and integrated $I(1)$, while all other variables in the analysis are $I(0)$.⁸ The ARDL methodology allows us to address this issue and to estimate both short-run and long-run relationships between variables without requiring pre-testing for cointegration (the only requirement being no variables $I(2)$) or transforming the $I(1)$ price index to make it stationary. Moreover, through the ARDL bounds test for cointegration (Pesaran et al., 2001), we can determine whether a long-run equilibrium relationship exists between natural gas demand and the price index.

⁷ For an in-depth analysis of the application of this methodology to natural gas, we refer the reader to Bernstein and Madlener (2011), while Hassler and Wolters (2011) and Kripfganz and Schneider (2023) provide excellent theoretical and practical indications on ARDL models.

⁸ Tables with ADF, PP, KPSS tests' results are reported in Appendix.

As anticipated in the Section on the data, the main explanatory variables are the weather-dependent variables HDD_t and SR_t to model the relationship between (lower) temperatures and (higher) natural gas consumption,⁹ and the price index. To control for seasonality in natural gas consumption, we include eleven monthly dummies δ_m and six daily dummies δ_d with $m \in \{2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12\}$ and $d \in$

⁹ Additional variables are sometimes included in the literature accounting for wind speed and/or humidity — e.g., Jamissen et al. (2024) and Ruhnau et al. (2023). However, as pointed out by Staffell et al. (2023), the largest drivers in errors' reduction are (1) population weighting of the variables, (2) HDDs, and (3) solar radiation. Additionally, Ruhnau et al. (2023) find that including wind speed does not improve in any appreciable way their model's performance, while wind's influence on the Restricted Error Correction Model of Jamissen et al. (2024) is negligible. It should also be noted that most of the northern regions of the Italian peninsula, characterized by lower average temperatures and high population density, are areas of the Po Valley where there is very little wind. Therefore, we opt for a more parsimonious model.

{2, 3, 4, 5, 6, 7}.¹⁰ We also include a linear time trend, $\delta \times t$, to account for any potential underlying trend in the dependent variable. Hence, we hypothesize the following relationship:

$$gas_t = \alpha_0 + \sum_{j=1}^J \alpha_j gas_{t-j} + \sum_{k=0}^K \beta_k HDD_{t-k} + \sum_{p=0}^P \gamma_p SR_{t-p} + \sum_{q=0}^Q \phi_q price_{t-q} + \sum_{d=2}^7 \xi_d \delta_d + \sum_{m=2}^{12} \psi_m \delta_m + \delta t + \varepsilon_t, \quad (2)$$

where lags correspond to days. By the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963), the coefficients on HDD, solar radiation, and the price index are numerically identical to those obtained from regressing de-seasonalized consumption on de-seasonalized controls – where de-seasonalization means projecting each variable onto the full set of monthly dummies, day-of-week dummies, and the linear time trend. Therefore, the estimated coefficients – and the elasticities derived from them – are identified from within-season, de-seasonalized variation, and are not confounded by the seasonal co-movement that the dummies already absorb.

This point is especially relevant for the HDD_t variable, which is not merely a proxy for the seasonal cycle. The monthly dummies absorb the average within-year temperature pattern – the fact that January is, on average, colder than July – but they cannot distinguish a warm January from a cold one, nor a mild winter from a severe one. The variable HDD_t captures precisely this cross-year, within-season variation in temperatures relative to the heating threshold T_0 , which the seasonal dummies leave untouched. The unusually mild winters of 2022/2023, 2023/2024, and 2024/2025, which are central to our identification, exemplify the variation that HDDs contribute beyond any fixed seasonal dummy. It is this within-season variation that makes the HDD_t variable informative about space-heating demand, over and above the mechanical annual cycle captured by the temporal dummies.

As Jamissen et al. (2024), we adopt a linear specification, assuming that the relationship between gas_t and HDD_t is linear (as in Kozarcanin et al. (2019) and Quayle and Diaz (1980)). Other papers adopt a log-log specification (e.g., Asche et al. (2012), Erias and Iglesias (2022) and Bernstein and Madlener (2011)), with the main advantage of allowing to immediately interpret the coefficient of the price variable as the average elasticity over the entire sample. However, a log-log specification in our case is not suited to our purposes for three distinct reasons.

1. The relationship between residential gas consumption and heating degree days is essentially linear in the data, as immediately suggested by graphical inspection. A simple univariate linear regression of consumption on HDDs already yields an R^2 of 95%.¹¹ Given that the data-generating process is linear in the key regressor, a log-log specification would introduce curvature artificially where none exists, at the cost of interpretability and without any gain in fit.
2. A log-log model yields a single, constant average elasticity throughout the sample period. We are instead interested in studying how the price elasticity of gas demand evolved in response to the 2022 energy crisis, an exercise that is feasible

assuming a linear demand curve, from which time-varying elasticities can be recovered at each point in the sample.

3. A log-log specification is undefined whenever any explanatory variable takes the value zero (as it is often the case with the HDD control), requiring an arbitrary rescaling in a non-linear relationship that may affect the results.

As it is well known, the ARDL model can be reparameterized as an Unrestricted Error Correction Model to conduct the Pesaran et al. (2001) bounds test for cointegration.¹² The unrestricted ECM's equation is:

$$\Delta gas_t = \alpha_0 + \delta t + \pi_{gas} gas_{t-1} + \pi_{HDD} HDD_t + \pi_{SR} SR_t + \pi_{price} price_t + \sum_{j=1}^{J-1} \theta_{gas,j}^* \Delta gas_{t-j} + \sum_{k=0}^{K-1} \theta_{HDD,k}^* \Delta HDD_{t-k} + \sum_{p=0}^{P-1} \theta_{SR,p}^* \Delta SR_{t-p} + \sum_{q=0}^{Q-1} \theta_{price,q}^* \Delta price_{t-q} + \sum_{d=2}^7 \xi_d \delta_d + \sum_{m=2}^{12} \psi_m \delta_m \quad (3)$$

where the null hypothesis of the test is the absence of any cointegrating relationship between the variables, hence:

$$H_0 : \pi_{gas} = \pi_{HDD} = \pi_{SR} = \pi_{price} = 0. \quad (4)$$

In all of our cases, the computed F-statistic is well above the upper bound's critical values calculated by Kripfganz and Schneider (2023) and all the approximate p-values are zero.¹³ Therefore, the null hypothesis of no cointegrating relationship between our variables is rejected at any significance level. As a result, the postulated functional form is a long-run relationship. In equilibrium, it must be that:

$$0 = \pi_{gas} gas_{t-1} + \pi_{HDD} HDD_t + \pi_{SR} SR_t + \pi_{price} price_t, \quad (5)$$

where in equilibrium $gas_{t-1} = gas_t$. Therefore, solving for gas_t , we can recover the long-run cointegrating relation as:

$$gas_t = \beta_{HDD} HDD_t + \beta_{SR} SR_t + \beta_{price} price_t, \quad (6)$$

where:

$$\beta_{HDD} = -\frac{\pi_{HDD}}{\pi_{gas}}, \quad \beta_{SR} = -\frac{\pi_{SR}}{\pi_{gas}}, \quad \beta_{price} = -\frac{\pi_{price}}{\pi_{gas}}. \quad (7)$$

The deviation from that long-run equation is:

$$ECT_t = gas_t - \beta_{HDD} HDD_t - \beta_{SR} SR_t - \beta_{price} price_t \quad (8)$$

and the β 's coefficients are the constant terms from the previous step. By construction $ECT_t = 0$ in equilibrium. We can now rewrite our Unrestricted Error Correction Model as:

$$\Delta gas_t = \gamma ECT_t + \sum_{j=1}^{J-1} \theta_{gas,j}^* \Delta gas_{t-j} + \sum_{k=0}^{K-1} \theta_{HDD,k}^* \Delta HDD_{t-k} + \sum_{p=0}^{P-1} \theta_{SR,p}^* \Delta SR_{t-p} + \sum_{q=0}^{Q-1} \theta_{price,q}^* \Delta price_{t-q} + \delta t + \sum_{d=2}^7 \xi_d \delta_d + \sum_{m=2}^{12} \psi_m \delta_m + \varepsilon_t, \quad (9)$$

which distinguishes between the long-run dynamics, collapsed into the error correction term, and the short-run Δ -dynamics. In the ECM, the

¹⁰ Therefore, the excluded (hence, reference) values are the month of January and the first day of the week, Sunday.

¹¹ De-seasonalizing both series – thereby purging the shared seasonality that mechanically inflates univariate goodness-of-fit – reduces the R^2 from 95% to 75%, indicating that the HDD–consumption relationship is not solely driven by common seasonal patterns. Although this finding is consistent with an underlying physical link between outdoor temperatures and space-heating demand, the existence of a well-fitting linear relationship should not be interpreted as sufficient evidence of a causal data-generating process.

¹² Our analysis falls under case 5 of the bounds tests as categorized by Kripfganz and Schneider (2023). We do not impose any further restrictions on the constant and time trend. Our results are completely unaffected by imposing any additional restriction on α_0 or δ .

¹³ Results of the bounds test are reported in Appendix.

coefficient γ captures how quickly deviations from the equilibrium are corrected, while the Δ terms and the associated coefficients capture transitory dynamics around the equilibrium path. In particular, to achieve convergence γ must be negative, significant, and smaller than one in absolute value.

5. Results

In this Section we discuss in detail the estimates obtained from the econometric model presented in the previous Section and highlight their relevance.

5.1. Estimates — Split samples

To test the hypothesis that the 2022 energy crisis triggered a radical shift in consumer behavior, we estimate the ARDL model from Eq. (2) and the ECM from Eq. (9) using two distinct subsamples: one covering the period before the crisis, and the other covering the crisis period. Specifically, the sample is split into 3622 observations for the pre-crisis subsample and 1492 observations for the crisis subsample, with December 2021 identified as the onset of the energy crisis. This date, significant at any confidence level, is determined via a Bai-Perron test applied to the model at a monthly frequency and has economic significance, as it marks the first substantial increase in our (lagged) price index. This surge resulted from a sharp decline in Russian exports to Europe, down to one-third of prior levels, coupled with an increasing share of LNG in national gas systems and a high LNG demand in Asia that pushed up the LNG contract prices, and weak European production, which together led to low storage levels. Moreover, in Europe, we have observed an increase in gas demand for thermoelectric production following the temporary closure of many French nuclear plants for maintenance. All these factors led to significant price spikes (Jamissen et al., 2024; Fulwood, 2022). This exercise, in particular, allows us to address two relevant issues:

- whether the long-run relationships between natural gas consumption and controls (weather conditions and price) change in the two samples;
- whether there is any relationship at all between consumption and the price index in the pre-crisis sample.

We begin by estimating the two ARDL models, with optimal lag selection based on the Bayesian Information Criterion (BIC) for each subsample. The criterion leads to an ARDL(15, 8, 1, 1) for the pre-crisis sample and to an ARDL(9, 8, 1, 0) for the crisis sample, where the numbers correspond to the number of lags of the gas, HDD, SR and price variables. Regression outputs are reported in Table 7. Both models are extremely effective at capturing the dynamics of natural gas demand, with R^2 of 99.5%. However, the economic interpretation of the estimated coefficients is not immediate, as each ARDL coefficient measures the partial effect of a lagged value of the explanatory variables on the level of the dependent variable, thus mixing up both short-run dynamics and the long-run equilibrium relationship between gas_t and the explanatory variables.

Therefore, we proceed by running the bounds test to assess the existence of a cointegrating relationship between the variables. We reject the null hypothesis of no cointegration at any significance level for both models, and thus we reparameterize them as the ECMs in Eq. (9). Then, we estimate the two ECMs, and the resulting coefficients are reported in Table 8. Immediately, we notice that:

1. the models do converge to a long-run equilibrium, as the estimated error correction terms ($\hat{\gamma}$) are significant at any confidence level, negative, and smaller than one in absolute value;
2. all estimated long-run coefficients – except the one on the price index in the pre-crisis sample – are significant at any confidence level.

Table 1

ECM results by sample.

ECT and long-run coefficients		
	Pre-crisis sample	Crisis sample
Demand (ECT, $\hat{\gamma}$)	−0.193***	−0.170***
Heating-degree days	12.690***	11.010***
Solar radiation	−2.115***	−1.762***
Price index	−0.020	−0.129***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In particular, $\hat{\gamma}^{pre-crisis} = -0.193$ and $\hat{\gamma}^{crisis} = -0.170$ indicate that the speed of adjustment towards equilibrium is $\left|\frac{1}{\hat{\gamma}}\right|$ days.¹⁴ In our setting, this means 5.2 days in the pre-crisis and 5.9 days in the crisis sample, a result close to that of Jamissen et al. (2024), who estimate a time of adjustment of 5.7 days for the German case. This result is of interest in light of the differences between the German and Italian natural gas markets.¹⁵ Finally, the estimated long-run coefficients – in particular the one on the price – will be employed in Section 5.2 to compute elasticities and to study their evolution over time.

Regarding the price effect, the bounds test rejects the null hypothesis of no cointegration between the variables in both subsamples, and the ECMs' outcomes are reported in Table 1. Our initial assumption is indeed confirmed: the price index plays no role in determining the long-run equilibrium before the sharp price increase of late 2021–2022. In particular, the long run coefficient is negative and significant at any confidence level only when estimated on the crisis subsample ($\hat{\beta}_{price}^{crisis} = -0.129$), while it is equal to -0.020 and insignificant in the pre-crisis subsample.¹⁶

Lastly, the coefficient on HDDs estimated on the pre-crisis sample ($\hat{\beta}_{HDD}^{pre-crisis} = 12.690$) is statistically different from the one on the crisis sample ($\hat{\beta}_{HDD}^{crisis} = 11.010$) at the 5% confidence level (p -value = 0.0349). The estimated coefficients indicate that before the crisis, one additional heating degree-day would lead to an increase in residential consumers' natural gas consumption of 12.690 Sm^3 , while, after the crisis, the same increase leads to an additional 11.010 Sm^3 in consumption. We conclude that the energy crisis altered consumers' reaction to lower temperatures. Notably, it lowered their consumption by reducing the marginal demand for each additional heating degree-day.¹⁷

5.2. Elasticities

Our next step is to compute and examine the evolution of the price elasticity of demand to assess the effects, if any, of the energy crisis on consumer behavior and responsiveness to price changes. Adopting

¹⁴ Notice that $\hat{\gamma}^{pre-crisis}$ and $\hat{\gamma}^{crisis}$ are statistically indistinguishable when we run a Wald test on the two coefficients.

¹⁵ For example, buildings in Germany are notoriously better insulated than in Italy, as pointed out by Kozarcanin et al. (2019). As a consequence, their estimated threshold temperature T_0 for Germany is 13.98°C, significantly lower than the 15.61°C estimated for Italy.

¹⁶ A Wald test is carried out on the non-linear transformation of the OLS parameters as formulated in Eq. (7) to test whether indeed $\beta_{price}^{pre-crisis} = \beta_{price}^{crisis}$. The associated p -value is 0.0695; therefore, we cannot reject the null at the 5% confidence level. This result, however, should be traced to the loss of statistical power caused by the sample split and to the modest magnitude of the coefficient itself. When the same ECM is run on the full sample of 5114 observations, the estimated coefficient $\hat{\beta}_{price} = -0.114$ is significant at any confidence level. Therefore, we conclude that these results, combined with the economic evidence already presented on the timing of the energy crisis, and the Bai-Perron test provide strong evidence of parameter instability consistent with a structural break, and that the significance of the β_{price} coefficient is entirely driven by the crisis sample.

¹⁷ The long-run coefficients on the solar radiation $\hat{\beta}_{SR}^{pre-crisis}$ and $\hat{\beta}_{SR}^{crisis}$ are instead statistically indistinguishable.

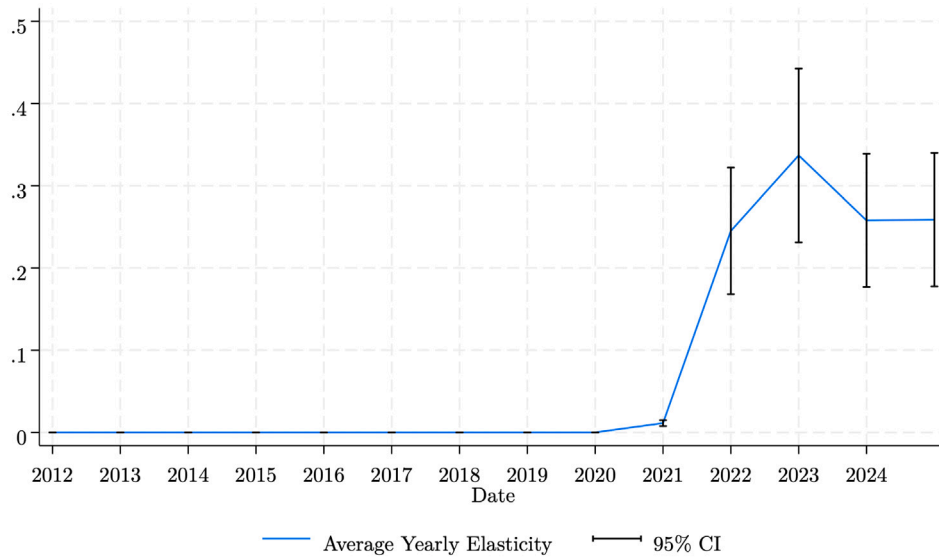


Fig. 6. Yearly average elasticity.

a linear specification implies that the elasticity varies at each point along the curve, with a high frequency variability and a clear seasonal pattern. To isolate meaningful figures that allow us to compare the evolution in consumers' behavior along the energy crisis, we focus therefore on an average yearly measure:

$$E_{p,y} = \left| \frac{\partial \text{demand}}{\partial \text{price}} \times \frac{\overline{\text{price}_y}}{\overline{\text{demand}_y}} \right| \quad (10)$$

$$= \left| \beta_{\text{price}} \times \frac{\overline{\text{price}_y}}{\overline{\text{demand}_y}} \right|,$$

where $\overline{\text{demand}_y}$ and $\overline{\text{price}_y}$ are the average demand and price index in a given year y , and β_{price} is the coefficient of the price index.

We first consider the total gas consumption in the expression, obtaining a first set of (unconditional) elasticities. Total consumption, however, in our econometric model depends not only on the price but also on weather conditions and temporal dummies. We can, therefore, interpret our estimate of the gas consumption equation as a demand curve that is linear in price, with an intercept that varies with the other control variables. Hence, to isolate the theoretical demand relationship between quantity and price (the demand curve), it is necessary to adjust consumption for the effects of the other control variables, netting out variations in quantities due to a shift in the demand curve from those occurring along the demand curve. Our second measure of (conditional) elasticities performs this exercise.

5.3. Unconditional elasticity — $E_{p,y}$

As $\hat{\beta}_{\text{price}}^{\text{pre-crisis}}$ is statistically indistinguishable from zero, the estimated elasticity is null until 2021. This finding also aligns with anecdotal reports that consumers made no adjustments whatsoever to their consumption before the crisis, as the price index was essentially stable.

Concerning the years of the energy crisis, we begin by estimating the ECM in Eq. (9) to obtain the coefficient $\hat{\beta}_{\text{price}}^{\text{crisis}}$, then we compute the average price elasticity of demand by year between 2021 and 2025. Thus, our estimate is computed using (10) with the $\hat{\beta}_{\text{price}}^{\text{crisis}}$ coefficient. The resulting time series is plotted in Fig. 6, where standard errors are computed with the delta method.

First of all, it should be noted that, in line with the existing literature, the price elasticity of natural gas demand is very low, as gas consumption is definitely inelastic to price changes — e.g., see Erias and Iglesias (2022) for a comprehensive cross-country study on the

price elasticity of natural gas demand and for an extended literature survey. Over our entire sample, its value ranges between 0 and 0.34, indicating that, at most, a 1% increase in the cost of natural gas leads to a modest 0.34% decrease in quantity demanded.

Nevertheless, despite the overall inelastic behavior of demand, we find evidence of a large increase in the estimated elasticities, which grow consistently in 2022 and 2023 and partially decrease in 2024–2025. In particular, between 2021 and 2023, the estimated value increases from virtually 0 in 2021 to 0.25 in 2022 and to 0.34 in 2023 and then declines to 0.26 in 2024 and 2025.

5.4. Conditional elasticity — $\tilde{E}_{p,y}$

In order to properly focus on the price-sensitive component of demand, we net out the shifts in quantities that depend on factors other than the price. In particular, given the model in Eq. (2), we estimate for the crisis period the ARDL(9,8,1,0) coefficients:

$$\hat{\delta}, \hat{\alpha}_j, j \in \{1, \dots, 9\}, \hat{\beta}_k, k \in \{0, \dots, 8\}, \hat{\gamma}_p, p \in \{0, 1\}, \quad (11)$$

$$\hat{\xi}_d, d \in \{2, \dots, 7\}, \hat{\psi}_m, m \in \{2, \dots, 12\},$$

and compute:

$$\tilde{Q}_t = \text{gas}_t - \hat{\delta}t - \sum_{j=1}^9 \hat{\alpha}_j \text{gas}_{t-j} - \sum_{k=0}^8 \hat{\beta}_k \text{HDD}_{t-k} - \sum_{p=0}^1 \hat{\gamma}_p \text{SR}_t - \sum_{d=2}^7 \hat{\xi}_d \delta_d - \sum_{m=2}^{12} \hat{\psi}_m \delta_m, \quad (12)$$

where it follows naturally that:

$$\tilde{Q}_t \simeq \alpha_0 + \phi \text{price}_t + \epsilon_t, \quad (13)$$

where $\tilde{Q}_t$ captures the price-sensitive quantity along the demand curve.

Given the consistency of the OLS estimator in this setting and the extremely large sample, estimated parameters are unlikely to deviate substantially from their population counterparts, lending credibility to this transformation. Therefore, we are confident that $\tilde{Q}_t$ truly captures the price-sensitive component of natural gas demand, and that its error term is not inflated by systematic deviations between estimated and population parameters. We now employ $\tilde{Q}_t$ to compute its price elasticity as:

$$\tilde{E}_{p,y} = \left| \hat{\beta}_{\text{price}}^{\text{crisis}} \times \frac{\overline{\text{price}_y}}{\overline{\tilde{Q}_y}} \right|, \quad (14)$$

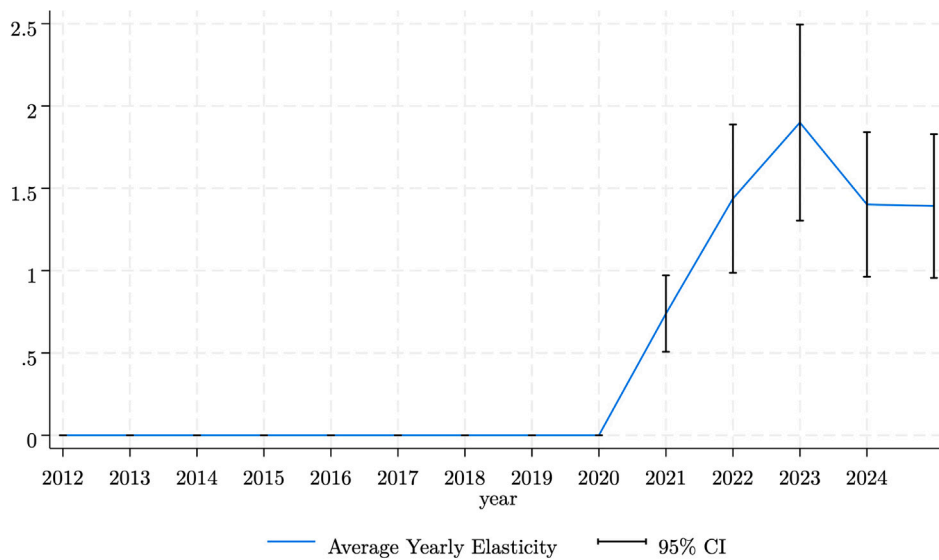


Fig. 7. Yearly average elasticity computed on $\tilde{Q}_t$.

where just as before the average quantity and price are computed by year y . The resulting time series is plotted in Fig. 7.

Our estimates for the 2021–2024 period signal that consumers reacted steadily to the 2022 energy crisis and – within the price-sensitive component of natural gas demand – even more than proportionally, as the elasticity computed on $\tilde{Q}_t$ jumps from 0.74 in 2021 to 1.44 in 2022, 1.90 in 2023, and 1.40 in 2024 and 1.39 in 2025, with a total increase of over +150%.

In summary, the results presented in Section 5.3 corroborate the existing literature by confirming that natural gas demand remains highly inelastic. However, we also observe a substantial and sustained consumer response, reflected in a marked increase of the estimated price elasticity. When focusing solely on the price-sensitive component of demand, it becomes clear that consumers are more responsive to price changes than previously thought. Still, this responsiveness is inherently constrained by non-price factors – notably, temperatures – which continue to exert the greatest influence on overall consumption.

Finally, we may observe that the estimated elasticities, referred to total consumption or to its price-sensitive component, are higher after the 2022 price spikes than before, taking as a reference a year with comparable price levels. This suggests a structural change in consumption behavior rather than a temporary adjustment to unprecedented circumstances.

6. Demand breakdown

In this Section we further investigate consumers' response to the energy crisis by dividing their consumption in two components: baseload and heating demand.

6.1. Methodology

It is an established fact that the demand for weather-dependent space heating accounts for most of natural gas consumption, with the residual component encompassing the demand for water heating and cooking, which is often assumed to be constant throughout the year in the literature — e.g., Kozarcanin et al. (2019). However, daily data on these two distinct components are not available in Italy and must be estimated from the total daily consumption of the distribution network published by Snam S.p.A. in its gas balances.

Adapting the methodology suggested by Snam's network code (Snam, 2003), we postulate that total natural gas consumption in day t (gas_t)

can be split into the demand for space heating ($heating_t$) and a residual baseload component ($baseload_t$) for water heating and cooking.

Then, we use the total daily consumption of gas in June and September of each year as a reference for baseload consumption. We select these two months because they are the first and last months of the year with essentially no heating consumption. Moreover, at least in Italy, commercial activity shutdowns and household vacations, which may significantly alter daily gas consumption patterns, are concentrated in July and August, while in June and September household activities are much more similar to those in the rest of the year. Hence, it seems reasonable to assume that total and baseload gas consumption coincide in these two months.

Moreover, daily gas consumption may differ during the week, possibly with some variation from one year to another. Hence, we compute for each year and day of the week the average baseload consumption in June and September, according to the following formula:

$$\widehat{baseload}_{d,y} = \frac{\sum_{d,m \in \{6,9\},y} gas_{d,m,y}}{n_d} \quad (15)$$

(15) estimates separately for each year the average daily baseload consumption in the seven days of the week, that is, the baseload consumption on day $d \in \{1, 2, 3, 4, 5, 6, 7\}$ of year $y \in \{2012, \dots, 2024\}$, taking as a reference for each day the average daily total consumption during the two months, $m \in \{6, 9\}$, in which there are no heating needs (where n_d is the number of occurrences of day d in the calculation).

It follows that the estimate (15) of baseload consumption in day d is the same for all weeks of year y , although it may differ among days and from one year to another. Finally, we define a variable $baseload_t$, i.e. the *actual base consumption*, as:

$$baseload_t = \begin{cases} \widehat{baseload}_t, & \text{if } \widehat{baseload}_t \leq gas_t, \\ gas_t, & \text{if } \widehat{baseload}_t > gas_t. \end{cases} \quad (16)$$

to correct for rare cases in which the estimated baseload exceeds the actual total consumption. Finally, having defined $baseload_t$, we can divide between the two components of demand, which are aggregated at the monthly level and plotted in Fig. 8.

6.2. Results

Applying the same regression analysis developed in Section 4, we estimate the ARDL and ECM models for the two components of demand separately, finding the optimal lag selection for each segment

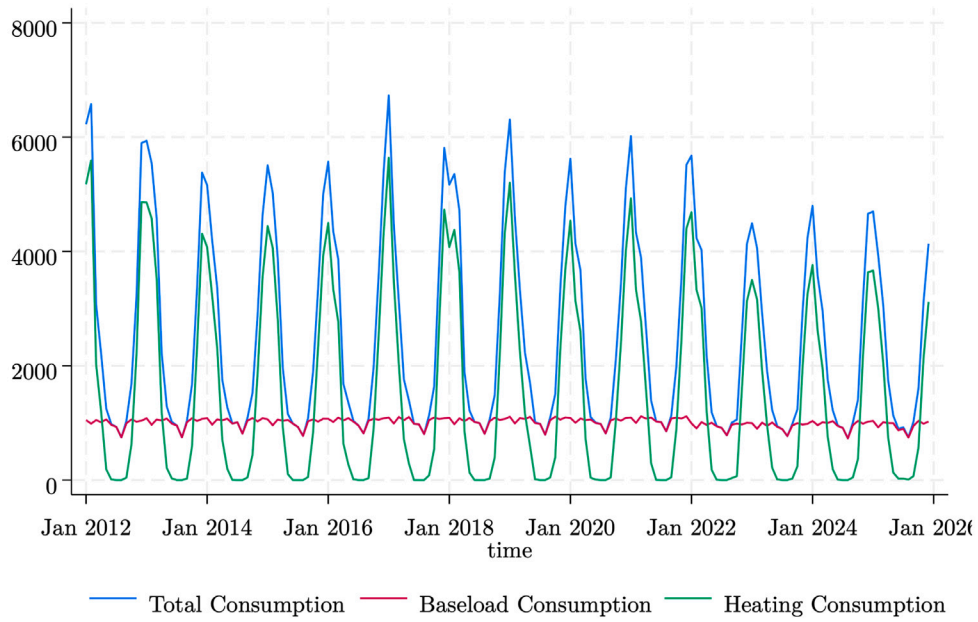


Fig. 8. Breakdown of total demand, monthly values (millions of Sm^3).

Table 2
ECM results by model.

	Heating demand		Baseload demand	
	Pre-crisis	Crisis	Pre-crisis	Crisis
Heating demand (ECT, $\hat{\gamma}$)	-0.189***	-0.180***		
Baseload demand (ECT, $\hat{\gamma}$)			-0.238***	-0.292***
Heating-degree days	12.769***	11.036***	-0.001	0.077
Solar radiation	-1.893***	-1.449***	-0.136***	-0.210***
Price index	-0.021	-0.120***	0.002	-0.009**

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of demand and obtaining $\hat{\beta}_{\text{price}}^{\text{baseload,crisis}}$ and $\hat{\beta}_{\text{price}}^{\text{heating,crisis}}$. Notably, for heating demand the BIC selects an ARDL(15, 8, 1, 1) for the pre-crisis subsample and an ARDL(9, 8, 1, 0) for the crisis subsample. For baseload demand, the BIC selects an ARDL(19, 0, 0, 0) for the pre-crisis subsample and an ARDL(12, 0, 0, 0) for the crisis subsample. Hence, heating demand behaves like total demand, as their determinants are the same. On the contrary, baseload demand does not respond to past levels of the climatic variables, and the best predictor of its value are indeed the lagged values of the dependent variable itself. Estimated long-run relationships are reported in Table 2, while estimated coefficients for the ARDLs (Tables 9 and 10) and for the ECMs (Tables 11 and 12) are reported in Appendix.

All ECMs converge, as the error correction terms $\hat{\gamma}$ are negative, smaller than one, and significant at any confidence level. However, the two models differ profoundly in the significance and economic interpretation of the estimated coefficients.

Consider first the price effect. The lack of any responsiveness of natural gas demand to the price index before the onset of the 2022 energy crisis is confirmed also breaking down total demand into its two components. After the crisis, instead, both price coefficients are different from zero and statistically significant, with $\hat{\beta}_{\text{price}}^{\text{heating,crisis}} + \hat{\beta}_{\text{price}}^{\text{baseload,crisis}} = -0.120 - 0.009 = -0.129 \approx \hat{\beta}_{\text{price}}^{\text{demand,crisis}} = -0.128$.¹⁸

¹⁸ Although the two price coefficients should add up to the price coefficient on the entire demand, that is $\hat{\beta}_{\text{price}}^{\text{demand,crisis}} = \hat{\beta}_{\text{price}}^{\text{heating,crisis}} + \hat{\beta}_{\text{price}}^{\text{baseload,crisis}}$, this condition holds only approximately, as the two models differ in their lag specifications from the one run on the entire residential demand. Similarly,

Moving to the effect of weather conditions, baseload consumption, as expected, is not sensitive to the HDD measure,¹⁹ which instead affects heating demand with an impact comparable to the one on total demand: $\hat{\beta}_{\text{HDD}}^{\text{heating,pre}} = 12.769 \approx \hat{\beta}_{\text{HDD}}^{\text{demand,pre}} = 12.690$ and $\hat{\beta}_{\text{HDD}}^{\text{heating,crisis}} = 11.036 \approx \hat{\beta}_{\text{HDD}}^{\text{demand,crisis}} = 11.010$. Moreover, the drop in the estimated HDD coefficient in the second period is statistically significant, suggesting that the 2022 energy crisis radically changed consumer behavior by lowering their additional demand for space-heating given the same drop in temperatures.

Therefore, we can conclude that:

- (1) heating demand is the weather-dependent component of natural gas consumption;
- (2) it is also the fraction of total demand that consumers could fine tune in response to the price spike caused by the 2022 energy crisis;
- (3) baseload consumption is essentially stable, independent of weather conditions and also highly inelastic to price.

To further validate these results, given the estimated coefficients $\hat{\beta}_{\text{price}}^{\text{heating,crisis}}$ and $\hat{\beta}_{\text{price}}^{\text{baseload,crisis}}$ – both statistically significant –, we can compute the respective yearly average elasticities as in Section 5.2. The resulting time series are plotted in Fig. 9. Immediately, we notice that, as already predicted, the weighted average of the two elasticities yields approximately the original price elasticity of demand, which would be in between the two lines.

The evidence collected confirms a familiar insight: space-heating demand, which represents 60% to 90% of total natural gas use, is the only component consumers can readily curb during a crisis simply by turning down their thermostats. By contrast, baseload demand remains relatively constant across years. Although it can be reduced,

the relationship between elasticities of total demand and its components holds only approximately: $E_{p,t}^{\text{demand}} = \omega_{\text{heating},t} \times E_{p,t}^{\text{heating}} + \omega_{\text{baseload},t} \times E_{p,t}^{\text{baseload}}$.

¹⁹ The coefficient $\hat{\beta}_{\text{SR}}^{\text{baseload}}$ is significant in both samples, but very small – around 1/12th of the coefficients $\hat{\beta}_{\text{SR}}^{\text{heating}}$. However, this result is merely due to the fact that the SR variable captures the small downward trend in baseload consumption that occurs during the summer months of July and August, where HDDs are zero or very close to zero.

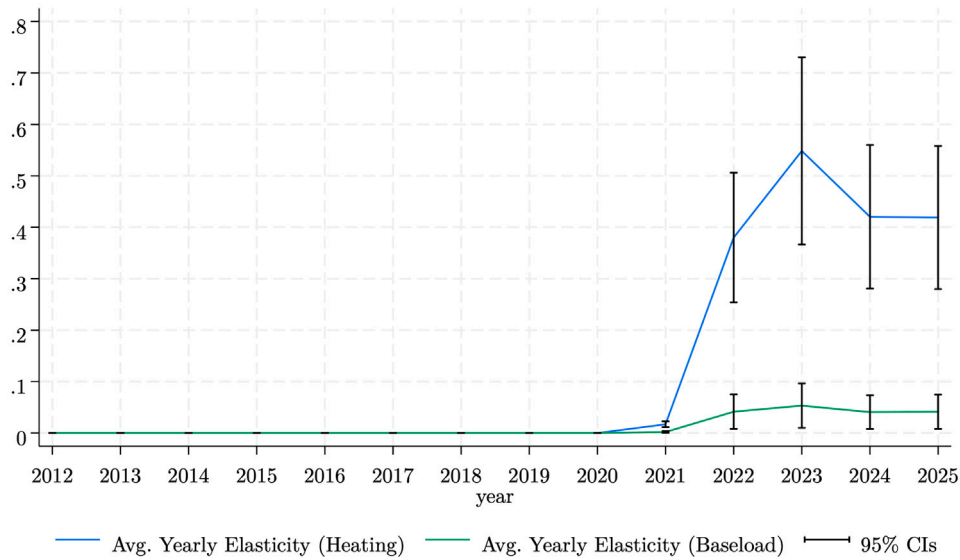


Fig. 9. Yearly average elasticity.

as happened in 2022, doing so is far more challenging and yields only marginal reductions in overall consumption. Therefore, the surge in estimated price elasticity for natural gas demand after the 2022 energy crisis primarily reflects consumers' ability to cut back on space heating.

7. Savings

Our results suggest that residential gas demand experienced a permanent change in behavior, becoming price sensitive and reducing the impact of weather conditions. In this Section, we perform a counterfactual exercise by comparing the actual consumption during the crisis with the one that would have been realized if consumption would have carried on according to the pre-crisis pattern. In this way, we may obtain a measure of how the change in behavior has enabled consumption savings in reaction to the high price spikes after 2021. We compute these savings both in volume and in monetary terms. We employ the ARDL(15, 8, 1, 1) model estimated on the pre-crisis sample to construct the pre-crisis parameters. Then, we employ these to forecast demand for the years 2022–2025. The difference between the actual and predicted demands yields our measure of estimated quantity savings. Finally, we multiply these saving by the average yearly price of natural gas for Italian residential consumers constructed by EUROSTAT to obtain our measure of financial savings.

7.1. The estimated model

In Section 5.1 we have estimated the Eq. (2) on the pre-crisis sample, i.e. before December 1st, 2021. A counterfactual consumption pattern can therefore be computed using the estimated pre-crisis coefficients, as reported in column 1 of Table 7 in the Appendix, and constructing a time series of the daily predicted demand for the observations from January 1st, 2022, to December 31st, 2025, as:

$$\begin{aligned}
 g\tilde{a}s_t = & \hat{\alpha}_0 + \hat{\delta}t + \sum_{j=1}^{15} \hat{\alpha}_j g\tilde{a}s_{t-j} + \sum_{k=0}^8 \hat{\beta}_k HDD_{t-k} + \sum_{p=0}^1 \hat{\gamma}_p SR_{t-p} + \sum_{q=0}^1 \hat{\phi}_q price_{t-q} \\
 & + \sum_{d=2}^7 \hat{\xi}_d \delta_d + \sum_{m=2}^{12} \hat{\psi}_m \delta_m,
 \end{aligned} \quad (17)$$

The resulting time series is aggregated at monthly resolution to ease visualization and plotted in Fig. 10.

Finally, the vertical distance between the two curves constitutes our measure of savings which can be computed as the difference:

$$savings_t = gas_t - g\tilde{a}s_t, \quad (18)$$

which is plotted in Fig. 11. Clearly, the greatest savings are achieved in the winter months of 2023, 2024, and 2025, whereas during the summer months our savings display values consistently almost null. This result confirms once again the by now established fact that the greatest contribution to the decrease in natural gas consumption originated from a reduction in the demand for space heating.

Our analysis indicates that consumers saved 1729 millions of Sm^3 in 2022, 3656 millions of Sm^3 in 2023, 2981 millions of Sm^3 in 2024, and 3569 millions of Sm^3 in 2025. These correspond to 18.28 TWh in 2022, 38.66 TWh in 2023, 31.52 TWh in 2024, and 37.73 TWh in 2025, or a total reduction of 10.32% with respect to the counterfactual consumption over 2022–2025.

We can also compute the savings in monetary terms. Since our price variable is an index, it is not fit for this purpose. Alternatively, we employ the semestral national average natural gas prices, in euro per Gigajoule, charged to medium size households — with annual consumption between 20 and 200 GJ. This price includes all components paid by consumers (energy, supply and network costs, VAT and taxes). It is computed and published by EUROSTAT for the years 2022, 2023, 2024, and for the first semester of 2025 (Eurostat, 2025). Estimated financial savings during the energy crisis amount to 2.27 billion euros in 2022, 4.27 billion euros in 2023, 4.29 billion euros in 2024, and 2.35 billion euros in the first half of 2025, for a total of more than 13 billion euros over the course of the crisis period, accounting for a reduction of 9.67% with respect to counterfactual spending.

Finally, it is worth highlighting how remarkable the savings achieved in the winter of 2024–2025 are. The January 2025 peak equals the record reached in January 2023 – at the height of the energy crisis – and even surpasses the 2024 high. Yet these savings occur against a decline in the level of the price index, whose values are markedly lower than those observed at the crisis peak (see Fig. 5). This combination strongly suggests that the behavioral adjustment initially triggered by soaring prices has endured: consumers continued to save natural gas even as prices eased. We therefore conclude that Italian households exhibit a clear change in consumption patterns: the shock of the 2022 crisis, which first compelled them to save through extremely high prices, now appears to be embedded in their everyday consumption choices.

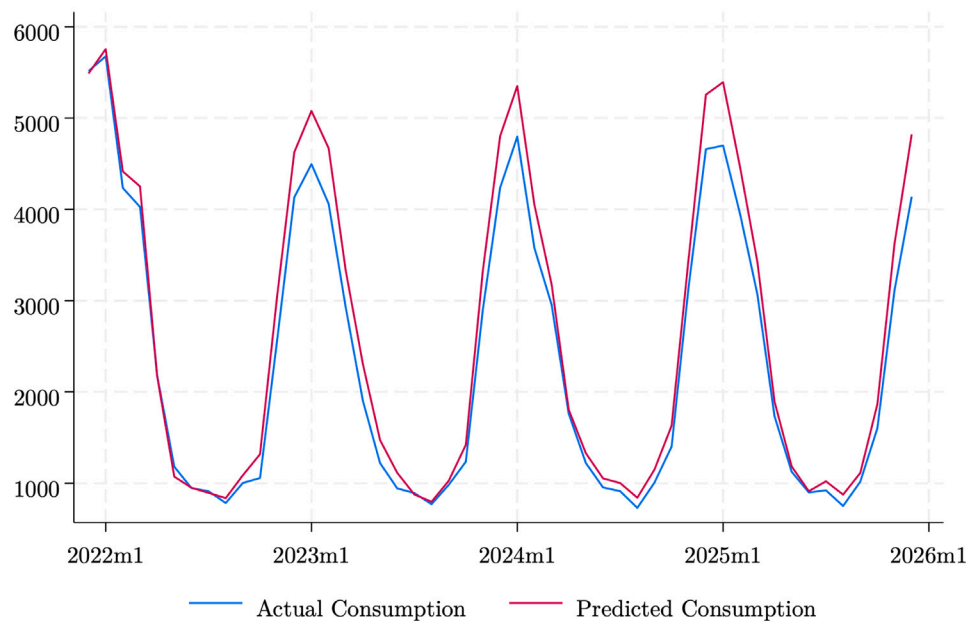


Fig. 10. Actual and predicted consumption, monthly values (millions of Sm^3).

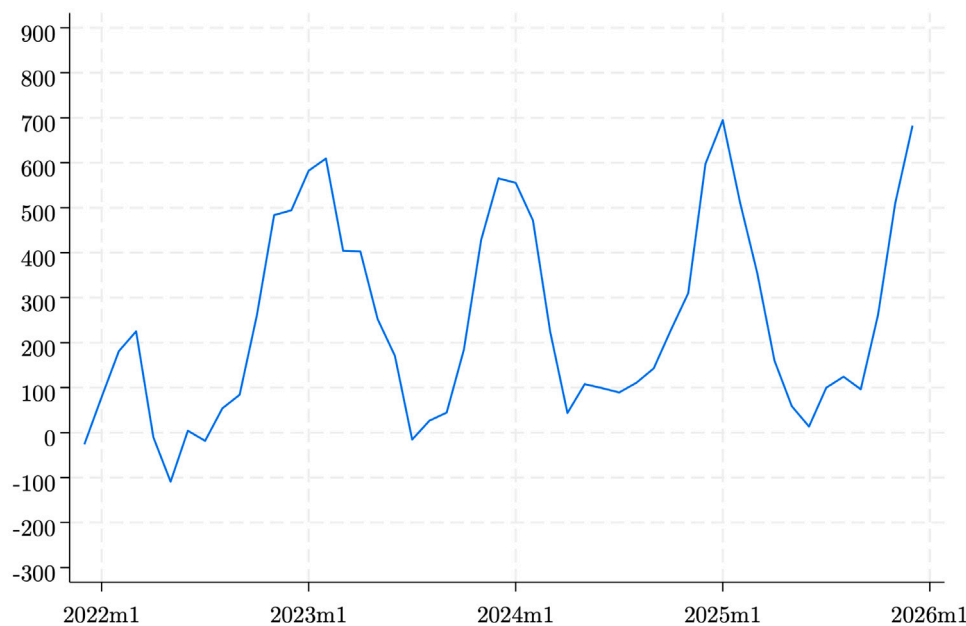


Fig. 11. Savings, monthly values (millions of Sm^3).

Whether this change is purely driven by behavioral change or leverages energy-saving investments realized in recent years, also due to generous incentives, is an open question we leave to future research.

8. Robustness checks and extensions

In this Section we carry out a number of robustness tests to build credibility in our methodology and data choices. We start by addressing the issue of the potential endogeneity of the price regressor in our reduced-form demand equation through an IV regression. Secondly, we test our estimates of savings by implementing a bootstrapping exercise and a sensitivity of the estimated coefficients to different training time windows. Moreover, we consider two extensions that include in the analysis additional factors that might have influenced the contraction in the volumes of gas not considered in our baseline model, namely

lockdowns due to the pandemic and government measures intended to promote gas savings.

8.1. Endogeneity and IV regression

In this Section we address the issue of endogeneity, which in reduced form estimates of demand is a potentially relevant problem. In our baseline model, we use three-month lagged prices, reflecting the lags in billing and price adjustment, which make the lagged price the relevant information for households in planning their current consumption patterns. We argue that this way we should be able to eliminate most concerns about simultaneity, as it is highly unlikely that the current daily demand for natural gas affects the average price three months earlier. Nevertheless, to address any outstanding concerns, we conduct an IV regression within the ECM model. We begin by constructing a

monthly TTF price index by averaging daily ICE Dutch TTF Natural Gas front-month futures prices within each calendar month.²⁰ Then, we instrument the 3-month lagged price index with the 6-month lagged TTF price index.

We choose this instrument since the TTF price stems from the exchanges at the Dutch trading hub (the Title Transfer Facility), the most liquid gas hub in Europe, which is unlikely to directly reflect specific demand conditions in the Italian gas market. As it intuitively has no direct effect on the prevailing demand conditions in Italy, any effect of the TTF price on Italian natural gas demand can only come through the effect of the TTF price on the price formed at the Italian hub (the “Punto di Scambio Virtuale”, or PSV), whose variation is reflected by our 3-month lagged price index. We take the 6-months lagged TTF price to account for the timing in the formation of the Futures contracts, and to align the peaks in the TTF and PSV prices during the energy crisis.

The IV estimation of the baseline ECM model for the crisis sample is successful, as the model is very strongly identified, with no evidence of under or weak identification whatsoever. Detailed tables with regression outputs are reported in Appendix. The estimated IV coefficient on the price index is -0.139 , slightly above the estimated value of -0.129 obtained from the baseline OLS model run on the crisis subsample in Section 5.1. If we extend the same analysis to the full sample, our estimates are even more precise: OLS yields a coefficient of -0.116 , while the IV regression yields -0.103 . This suggests that any difference between the full-sample and crisis estimate can be traced to the smaller sample size in the crisis subsample, which reduces the precision of the estimated coefficients.

In conclusion, the evidence already presented in Section 3.4 and the strong results of the IV regressions indicate that endogeneity poses no significant threat to our identification strategy and that our estimated elasticities are robust.

8.2. Robustness of estimated savings

We conduct two distinct robustness exercises to assess the reliability of our counterfactual savings estimates. The first addresses parameter uncertainty: a single ARDL estimation yields point estimates of the model coefficients, but these are subject to sampling variability, and one may legitimately question whether the implied savings could plausibly be zero under alternative parameter draws. We address this concern by implementing a residual block bootstrap.

The second tests the robustness of the results to different training windows. The counterfactual is constructed using a model estimated on the full pre-crisis sample, from 2012 through November 2021, and one may wonder whether estimated savings depend on which pre-crisis years are included in the estimation. We address each concern in turn.

8.2.1. Bootstrap confidence intervals for estimated savings

To quantify the uncertainty surrounding the counterfactual savings estimates, we implement a residual block bootstrap. The procedure preserves the serial dependence of daily gas consumption data by resampling blocks of consecutive residuals rather than individual observations. Specifically, we partition the $\hat{u}_t$ residuals from the baseline ARDL(15,8,1,1) model estimated over the pre-crisis sample into non-overlapping blocks of 30 days. Denoting by N the number of pre-crisis observations with valid residuals (i.e. excluding, the first 15 observations lost to initialize the lag structure), we draw $[N/30]$ blocks with replacement to construct a synthetic residual series of length N . For each of the $B = 10,000$ bootstrap replications, we add the resampled residuals to the baseline fitted values to obtain a synthetic dependent

Table 3

Bootstrap confidence intervals for counterfactual gas savings (millions Sm³).

Year	Point estimate	Median	95% confidence interval	
			Lower	Upper
2022	1729	1517	1012	2037
2023	3656	3028	2178	3899
2024	2981	2655	2110	3211
2025	3569	3184	2619	3764
2022–2025	11,935	10,390	7934	12,896

Notes: Confidence intervals derived from 10,000 residual block bootstrap replications with block size of 30 days. The point estimate is the savings implied by the baseline ARDL(15,8,1,1) estimated on the full pre-crisis sample; the median and confidence interval reflect parameter uncertainty across bootstrap re-estimations.

variable $y_t^* = \hat{y}_t + \hat{u}_t^*$, re-estimate the ARDL model on this synthetic pre-crisis sample, and then compute a dynamic out-of-sample forecast over the crisis period 2022–2025 using the re-estimated coefficients. Yearly savings in each replication are defined as the difference between the bootstrap counterfactual forecast and actual consumption, mirroring the point-estimate calculation. Percentile-based 95% confidence intervals are constructed from the resulting empirical distribution of 10,000 savings draws.

The results, reported in Table 3, confirm that the estimated savings are statistically precise and economically large over all four years. The point estimate of cumulative savings over 2022–2025 is 11,899 million Sm³, with a bootstrap median of 10,354 million Sm³ and a 95% confidence interval of [7899; 12,858] million Sm³. Year by year, the lower bound of the confidence interval ranges from 1012 million Sm³ in 2022 to 2585 million Sm³ in 2025, confirming that the demand response was not only immediate but also persistent. Overall, the bootstrap exercise corroborates the robustness of the counterfactual: even at the lower end of the confidence interval, cumulative savings exceed 7.9 billion Sm³, ruling out the hypothesis that the apparent demand reduction reflects estimation uncertainty rather than a genuine behavioral response to the energy crisis. Finally, bootstrap distributions of yearly and total savings are visualized in Figures 15 and 16 in Appendix.

8.2.2. Sensitivity to the training window

To assess whether the estimated savings are sensitive to the choice of the training window, we replicate the counterfactual exercise under an expanding-window scheme. Starting from a minimum training sample of five years (2012–2016),²¹ we re-estimate the ARDL model at each successive cutoff through 2021, allowing the BIC to select the optimal lag structure at each step (with a maximum of 15 lags), and then dynamically forecast residential gas demand over 2022–2025 using actual realizations of all exogenous variables. The 2012–2021 window replicates the baseline specification. Table 4 reports annual and cumulative savings for each training window. Figure 14 (Appendix) plots the different estimated savings patterns by training window.

The expanding-window robustness check reveals that two training windows yield savings estimates that should be treated as outliers. The 2012–2016 window produces a long-run price coefficient of approximately -0.073 , roughly three times larger in absolute value than those obtained from all other windows. Because this training period covers exclusively a phase of monotonically declining prices, the model overstates the mechanical demand response to price; the resulting counterfactual is therefore too close to actual consumption, and the corresponding savings estimate of 1429 million Sm³ should be interpreted as a lower bound. The 2012–2018 window, conversely, is the only one yielding a positive long-run price coefficient ($+0.015$); when extrapolated to the high-price crisis period, this sign reversal mechanically

²⁰ Daily prices are sourced from [Investing.com](https://www.investing.com/commodities/ice-dutch-ttf-gas-c1-futures) for the ICE Dutch TTF Natural Gas front-month futures contract (ticker: TFMbmc1), available at <https://www.investing.com/commodities/ice-dutch-ttf-gas-c1-futures>.

²¹ This is the first window to yield meaningful coefficients, e.g., the coefficient on the lagged price index is positive in all shorter windows.

Table 4
Estimated savings by training window (millions Sm³).

Training sample	2022	2023	2024	2025	Total
2012–2016	–256	398	419	867	1429
2012–2017	1202	2382	2164	2730	8478
2012–2018	2977	5662	4520	5257	18,416
2012–2019	1241	2776	2549	3162	9728
2012–2020	944	2423	2152	2695	8214
2012–2021 ^a	1729	3656	2981	3569	11,935

^a Baseline specification.

inflates the counterfactual, and the corresponding savings estimate of 18,416 million Sm³ should be interpreted as an upper bound. Notably, the remaining windows – 2012–2017, 2012–2019, and 2012–2020 – yield price coefficients in the range of –0.022 to –0.048, and their savings estimates cluster between 8214 and 9728 million Sm³.

Our baseline specification yields a savings estimate which is moderately above the estimates produced by the three most stable windows but remains well within the bounds defined by the two outlier windows, providing reassurance that our main measure of savings is not an artifact of the training window choice.

Taken together, these exercises indicate that our savings estimates are not driven by any particular realization of sampling noise in the coefficient estimates, nor are they excessively sensitive to the exact end-point of the training sample. The model's pre-crisis demand relationship is identified stably, and the baseline estimates, using the full available pre-crisis history, represent a sufficiently robust benchmark.

8.3. Covid-19 Pandemic and lockdowns

The Covid-19 Pandemic could have severely affected the patterns of natural gas consumption of both the residential sector and small commercial activities. At the height of the first lockdown, the whole Italian population, with very few exceptions, was essentially forced to remain in their houses from March 9th to June 3rd, 2020, rather than staying at the workplace or school. Similarly, the vast majority of businesses and productive activities were shut down. Ex ante, one could expect an impact on the patterns of natural gas consumption. Conversely, the lockdown encompassed only the last month of the heating season (mid-March to April 15th), the one with the notoriously declining and lowest demand for space heating. Therefore, the overall effect of the lockdown on our analysis is ambiguous and must be investigated further, as the model used to forecast the counterfactual gas demand during the energy crisis is indeed trained on data encompassing the lockdown.²²

We develop two alternative but similar tests to verify the potential impact of lockdowns. First, we introduce in our baseline model the four dummies separately to capture lockdown-specific fixed effects. Second, we estimate the model excluding altogether from the baseline regression all observations belonging to either lockdown period.

The two strategies yield similar results: when controlling for lockdown FEs, the coefficients estimated by the model (in particular, the one on the price index) are essentially unaffected across all four FE dummies. When the lockdown observations are dropped altogether

²² While the lockdown started with the most restrictive measures on March 9th, at the end of the period, the rules were progressively softened. May 4th marks the beginning of the so-called "Phase 2" in the government's management of the emergency and the end of the harshest lockdown measures. On May 18th, services, social activities, and within-region travels were again allowed, while on June 3rd all restrictions on national mobility were lifted. To test for the lockdown effect, we use therefore three different temporal dummies referring to the first lockdown – respectively extended to May 4th, May 18th and June 3rd 2020 – and a single dummy for the second lockdown – extending from November 6th to December 13th 2020.

from the sample, similar results hold: coefficients are substantially unaffected across all specifications. For this reason, the savings estimated in Section 7 are largely unaltered by the inclusion/exclusion of the Covid-19 lockdown from the estimation sample, and if anything our estimates are conservative, as the exclusion of the lockdown samples produces slightly higher savings (see Figure 12 in the Appendix).

Taken together, these results provide strong evidence that our analysis is not affected by the Covid-19 pandemic, which, moreover, does not appear to have significantly affected natural gas consumption patterns.

8.4. Government intervention

Starting from the spring 2022, the European Commission approved plans and regulations to cope with the energy crisis. The governments of the EU member states introduced their own regulations to soften the impact of price spikes on final bills and promote savings in gas consumption. The Italian Government undertook several measures between 2022 and 2023 to foster savings. With the Ministerial Decree No. 383 of October 6th, 2022, the Italian government intended to limit gas consumption for most residential buildings. The beginning of the heating season was postponed from October 15th to October 22nd, 2022, the end of the heating season was anticipated from April 15th to April 7th, 2023. Moreover, from October 22nd, 2022, to April 7th, 2023, thermostats' maximum allowed temperature was lowered from 20°C to 19°C.²³

Since these measures, which could directly affect gas consumption volumes, temporarily overlap with the increase in gas prices, it is important to disentangle households' reaction to more expensive bills from the adjustments in consumption to comply with the restrictions.²⁴

To control for the effects of these policy measures, we include three temporal dummies corresponding to the different components of the restrictions. We find that the shortening of the heating season had essentially no effect on consumption and on estimated coefficients. In other words, cutting the first and last weeks of the heating season (which were also characterized by above-average temperatures in 2022 and 2023) had no effect whatsoever in fostering savings.

The dummy for the reduction in the maximum allowed temperature, instead, partially affects our results. The dummy itself is not statistically significant at any confidence level. However, the estimated price coefficient drops from –0.129 in the baseline model to –0.109. This lower coefficient would imply a reduction in the peak elasticity point estimate from 0.34 to 0.28 (see Figure 13 in the Appendix).

9. Conclusions

This study provides the first comprehensive econometric analysis of Italian residential natural gas consumption at the turn of the 2022 energy crisis, employing daily data spanning from 2012 to 2025. Our findings reveal a profound structural transformation in consumers' behavior that extends far beyond the immediate crisis period, with implications that continue to shape energy consumption patterns today.

The empirical evidence unequivocally demonstrates that Italian households exhibited significant responsiveness to the unprecedented price shocks of 2022–2023. Prior to December 2021, natural gas demand was driven by weather conditions and was essentially price-inelastic, with consumers showing no measurable response to price

²³ Although the Decree did include provisions for controls and sanctions for buildings not complying with the new regulations, the extent to which the Decree's guidelines were effectively enforced remains dubious. This proves particularly true regarding the reduction in thermostats' maximum temperature, as there are around 26 million private households in Italy.

²⁴ For instance, Fabra et al. (2025) find that in the electricity Spanish market, the government measures, more than the price, account for the most important factor in affecting the reduction in energy consumption.

changes. However, the crisis triggered a fundamental shift in consumption behavior, with price elasticity increasing from virtually zero to 0.34 by 2023, a transformation that persists even as prices have moderated. The increase in elasticity is even more pronounced when computed for the price-sensitive component of demand, reaching a maximum of 1.90.

The decomposition of total demand into heating and baseload components reveals that the crisis response was highly segmented. Space heating demand, representing 60%–90% of total consumption, proved to be the primary adjustment mechanism, with consumers reducing heating consumption by approximately 1.6 million cubic meters per additional heating degree day compared to pre-crisis levels. In contrast, baseload consumption remained relatively stable, confirming that essential uses of natural gas, such as cooking and water heating, are indeed difficult to curtail.

The magnitude of achieved savings is remarkable: Italian households reduced consumption by approximately 11.9 billion cubic meters between 2022 and 2025, corresponding to 13 billion euros in financial savings. These figures underscore both the severity of the crisis and the substantial capacity for demand-side adjustment when economic incentives are sufficiently strong.

These savings are mostly due to consumers' genuine response to price spikes, whereas the policy measures introduced to incentivize gas savings have played a minor role. Similarly, lockdowns imposed during the Covid-19 pandemic do not seem to have significantly altered the gas consumption patterns.

Our analysis reveals compelling evidence of persistence in the consumption pattern. The sustained high levels of savings observed in late 2024 and early 2025, despite significantly lower price levels, suggest that the crisis induced lasting changes in consumption habits. These preliminary findings challenge conventional assumptions about the temporary nature of crisis-induced behavioral adjustments and point to the emergence of a new normal in Italian energy consumption patterns. Whether this change reflects investment in energy-efficient devices or purely behavioral adaptation – or both – remains an open question beyond the scope of this paper which is left to future research.

Several limitations of our analysis, which derive from the data available, deserve acknowledgment. The national-level aggregation of data prevents us from examining regional variations in crisis response, which may be substantial given Italy's diverse climate and economic conditions. Whenever more disaggregated data are available, future research should prioritize disaggregated analysis at the regional or provincial levels to better understand the heterogeneity of crisis responses across different contexts.

Additionally, our data source on residential consumption might be biased by the inclusion of small commercial activities in the gas balances, as these may exhibit consumption patterns that may differ in part from those of true residential consumers. We have, however, offered arguments that this divergence should not be substantial, and the small fraction of small commercial activities in the overall numbers should not significantly affect the results.

Finally, the question about the persistence of Italian consumers' virtuous behaviors remains open, as we are limited in our sample to data spanning at most until 2025. Once additional post-crisis evidence becomes available, it will be possible to properly test whether Italy has indeed achieved a structural and durable improvement in gas consumption and to what extent the heavily subsidized investments in energy efficiency may be a factor in this change.

CRediT authorship contribution statement

Michele Polo: Writing – original draft, Methodology, Conceptualization. **Tommaso Rocuzzo:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Online Appendix. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.eneco.2026.109438>.

Data availability

All data used in this study are open source and fully retrievable. To ensure transparency and reproducibility, we have established a dedicated GitHub repository where all datasets, analysis code, and direct links to every source are provided. The repository is accessible at <https://github.com/troccuzzo/Polo-Rocuzzo-2026>, and it includes:

- processed data files;
- complete code for analysis and figure generation;
- README with detailed documentation;
- direct links to all original data sources.

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