REVISITING ENERGY DEMAND ELASTICITY: THE POWER OF REGIME SWITCH

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Revisiting Energy Demand Elasticity: The Power of Regime Switch [1]

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Abstract:

This paper estimates residential electricity and gas price elasticities during the recent energy crisis, a period of exceptionally large price increases, using VAT-inclusive prices that reflect both market dynamics and policy-induced variation. We compare a standard constant-elasticity (log–log) specification with two regime-switching approaches: a structural break model distinguishing pre- and post-crisis elasticities, and a threshold model allowing elasticities to vary with the price level. While widely used, constant-elasticity models may poorly approximate demand under large price changes; in this context, regime-switching specifications provide complementary insights into how consumer responses vary across price regimes. Our results reveal distinct patterns across markets: for electricity, elasticity is lower in high-price periods than in low-price regimes, whereas for gas, only high-price periods induce significant reductions in consumption.

Key words: Energy demand; Price elasticity; Energy crisis; Residential energy consumption; Constant elasticity model; Structural break; Threshold model; Regime-switching models; Energy pricing.

JEL No: D12, Q41, Q48, C23

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1. Introduction

Energy prices started to rise in July 2021, driven by the global economic recovery following the COVID-19 pandemic. The situation deteriorated further in February 2022 when Russia's invasion of Ukraine triggered a sharp increase in gas and electricity prices. Overall, these developments resulted in an average price increase of 173.9% for residential electricity and 196.6% for residential gas, compared to the pre-crisis period. The magnitude and unexpected nature of these price increases provide an interesting empirical setting to estimate energy price elasticity.

Residential gas and electricity demand is widely found to be price inelastic, particularly in the short run. However, results are highly influenced by the type of data, the model specification, and the estimation techniques employed. For instance, studies relying on aggregate data often report smaller elasticities than those using micro-level household data (Labandeira et al., 2017; Mubiinzi et al., 2024). Most of this empirical literature relies on relatively small price variations, and evidence on household responses to large price shocks remains scarce.

Only a limited number of studies estimate energy price elasticity in the context of substantial price changes. For example, Alberini et al. (2020) exploit a quasi-experimental setting to examine residential gas demand in Ukraine during a period when tariffs more than tripled within a single month following political tensions between Ukraine and Russia. Their results indicate a short-run price elasticity of −0.16. Byrne et al. (2021) analyze household electricity demand responses to large price decreases using a randomized experimental design. In this study, households were randomly assigned to receive discounts of up to 50% on their total electricity bill and up to 95% on the marginal price of electricity for one month. The authors find that electricity consumption remained essentially unchanged.

This paper extends this literature by examining the electricity and gas price elasticity of Belgium households during the recent energy crisis. We estimate this using three alternative model specifications. First, we employ a constant elasticity model, which is widely used in the literature (Labandeira et al., 2017; Mubiinzi et al., 2024) and assumes that the responsiveness of energy demand to price remains stable over time and over the price range. Second, we estimate a structural break model in which the price elasticity is allowed to change at the onset of the energy crisis (i.e., July 2021). Third, we implement a threshold model in which the price elasticity varies depending on whether energy prices are above or below a certain level. In this specification, the threshold is estimated endogenously from the data.

Accounting for structural breaks can be important when estimating demand elasticities in energy markets. If the underlying relationship between variables changes over time, models that impose parameter stability may yield biased or inefficient estimates of regression coefficients (Perron, 2010). This issue is particularly relevant in electricity markets where regulatory reforms, price shocks, and technological changes frequently induce structural changes in demand relationships (Liddle, 2023). A large share of the energy demand literature estimates price elasticities within a cointegration framework that identifies stable long-run relationships between energy consumption, prices, and income while accounting for structural breaks (see, for instance, Yamaguchi, 2007; Pellini, 2021; Arčabić et al., 2021). However, while these approaches account for potential shifts in the long-run equilibrium relationship, they typically treat the price elasticity parameter as constant, implying that structural changes affect the level or trend of demand but do not alter its responsiveness to prices. By contrast, another strand of the literature estimates time-varying elasticities, allowing the responsiveness of demand to prices to evolve over time and thereby capture gradual changes in the price–demand relationship. (e.g., Liddle et al., 2020; Gao et al., 2021). A structural break model can be viewed as a special case of time-varying coefficient models in which the coefficients shift discretely at specific break points, thereby explicitly accounting for regime changes. To the best of our knowledge, only Blignaut et al. (2015) estimate a structural break model for electricity price elasticity. They analyze electricity demand elasticities across several industrial sectors in South Africa, examining behavioral changes following the 2007–2008 global energy crisis and the South African electricity tariff restructuring of 2008–2009. Their results indicate that when electricity prices were historically low, consumption was largely insensitive to price changes; however, after the crisis and tariff reform, industrial consumers became significantly more price responsive. Structural break approaches have also been applied in gasoline markets. For example, Akakpo & Barla (2017) identify two breakpoints, corresponding to three distinct price elasticity regimes.

Beyond time-based structural breaks, threshold models allow structural changes to occur when a key variable crosses a certain threshold. These models have been widely applied in energy economics to capture nonlinear responses of energy demand to key determinants. Early applications mainly focus on climatic factors, such as the well-documented U-shaped relationship between electricity consumption and temperature, where threshold models identify the temperature level at which demand regimes change (e.g., Bessec and Fouquau, 2008; Moral Carcedo and Vincens-Otero, 2005; Lee and Chiu, 2011). Other studies extend this approach to economic variables such as income and energy prices. Those studies find a positive relationship between electricity consumption and real income, with income growth in lower-income countries leading to a faster increase in electricity demand than in higher-income countries (Lee and Chiu, 2011; Fouquau et al., 2009). At the micro level, Charlier and Kahouli (2019) apply a panel threshold model to French households and show that price elasticities differ across income regimes. However, studies using energy prices as the threshold variable provide mixed evidence. For example, Kani et al. (2014) find that natural gas demand in Iran becomes more price responsive when prices are higher, whereas Nawaz et al. (2014) report that electricity demand in Pakistan becomes largely insensitive to price above a certain threshold. Similarly, Gabreyohannes (2010) shows that small tariff changes have little effect on electricity consumption in Ethiopia, while large price increases trigger stronger demand responses. Overall, there is no clear consensus on how price-based regimes affect energy demand, and existing studies generally examine contexts with relatively moderate or regulated price changes. By contrast, our analysis focuses on the exceptional price surge observed during the 2022 European energy crisis, providing a unique setting to reassess potential price threshold effects in electricity demand.

The latter two regime-dependent approaches allow us to investigate whether households respond differently to energy prices when prices are high compared to when they are low. When households face substantial price increases, they may adopt stronger adjustment strategies. For example, they may invest in more energy-efficient technologies, such as installing heat pumps, improving home insulation, or replacing older appliances with more efficient models, which typically involve significant upfront costs and may only become economically attractive when energy prices reach sufficiently high levels. Conversely, an alternative mechanism may explain a decline in responsiveness when prices continue to increase. Ito et al. (2018) show that households initially adapt to higher prices by improving the energy efficiency of their appliance usage. However, once relatively simple energy-saving adjustments have already been implemented, further reductions in energy use become more difficult. Additional decreases in consumption typically require households to upgrade their stock of appliances to more energy-efficient technologies, a process that involves time and investment (Rapson, 2014; Sahari, 2019). Consequently, the marginal responsiveness of energy demand to further price increases may diminish, at least in the short run. In this paper, we assess which pattern dominates for residential electricity and gas demand.

Our results show that the commonly used constant-elasticity specification may provide a misleading representation of demand responses when price variation is high. In our data, most price variation occurs during the energy crisis period, while prices remain relatively stable beforehand. As a result, the constant-elasticity estimate is largely driven by observations from the high-price period and may therefore fail to capture typical consumer responses under normal market conditions. This highlights an important limitation of constant-elasticity demand models when applied to environments characterized by large and abrupt price fluctuations.

Our analysis complements the findings of Hindriks and Serse (2022), who analyze a similar dataset but focus exclusively on the pre-crisis period, a context characterized by relatively limited price variation. While they estimate a constant-elasticity model and obtain statistically significant price elasticities consistent with the existing literature, our analysis extends this framework to a setting with substantial price increases during the energy crisis period, allowing us to assess the validity of the constant-elasticity assumption under conditions of pronounced price shocks.

We further show that demand responses to energy prices may be nonlinear and regime-dependent in both electricity and gas markets. For electricity, price elasticity is statistically significant across regimes but smaller in magnitude during high-price periods compared to the low-price periods, indicating a weakening of consumer responsiveness as prices rise. For gas, in contrast, price elasticity is only statistically significant in the high-price range, suggesting that consumers adjust their consumption primarily when prices exceed a certain threshold. Overall, the results highlight the relevance of considering threshold effects when estimating price elasticity for energy markets.

The remainder of this paper is structured as follows. Section 2 describes the data and presents summary statistics. Section 3 outlines the methodology underlying the three empirical models used in the analysis. Section 4 presents the empirical results. Section 5 examines the sensitivity of the structural break date to alternative candidate dates. Finally, Section 6 concludes.

2. Data description

In Belgium, the electricity and gas bill paid by end consumers consists of several distinct components: the energy cost, transmission and distribution charges, and various taxes and surcharges, all of which are subject to value-added tax (VAT). These tariffs generally follow a two-part structure comprising a fixed fee, payable irrespective of consumption, and a variable component proportional to the volume of energy used (i.e., a flat rate per kilowatt-hour). This study concentrates on the variable component (i.e., the marginal price) which has exhibited substantial volatility, particularly during the recent energy crisis. Notably, most of this volatility stems from fluctuations in the energy cost. Under typical conditions, the energy cost represents slightly less than 30% of the final consumer bill, but during the energy crisis, it increased to approximately 50%.

The energy price data used in this study is provided by the Commission for the Regulation of Electricity and Gas (CREG), Belgium's federal energy regulator. This data corresponds to the dataset underlying the CREG Scan, an online tool that allows end consumers to assess whether the price of their electricity or gas contract is above or below prevailing market levels. The database contains the complete set of electricity and gas contracts—both current and historical—submitted each month by all energy suppliers active on the Belgian market, covering the period from January 2014 to August 2024. Because all providers are required to transmit their updated tariff sheets to CREG, the dataset offers detailed information on the prices and contractual conditions available to new customers at any point in time.

In addition to the energy cost component, for electricity, the dataset includes two taxes whose amounts vary across regions and across contracts, as these charges are freely determined by the energy suppliers: the green certificate fee and the cogeneration fee. Moreover, each contract specifies different prices depending on the type of electricity meter installed at the consumer's premises. Consistent with CREG's own tariff comparison methodology[3], this study focuses on the standard meter category, using a uniform rate for day and night consumption.

For electricity, there are three types of contracts: fixed, variable, and dynamic. We focus on the former two, as the latter is not common and requires customers to be equipped with a smart meter. For gas, only the first two types of contracts exist. Further note that the energy crisis reshaped the structure of available contract types. Due to high wholesale price fluctuation and uncertainty, fixed-price contracts gradually disappeared from the market. Variable contracts became dominant, though often with significantly higher markups than in the pre-crisis period.

Consumers with a fixed contract face no price variation and pay a constant price per kWh for the whole duration of their contract, typically 1 year. Those who signed a variable contract experience price variation according to an indexation formula[4], which is indexed on a quarterly or a monthly basis. All coefficients of the indexation formula stay constant during the whole duration of the contract. Note that during the energy crisis, the indexation formula regularly changed for new consumers. That is, for the same product, in a given month, we observe different prices: the ones based on the old indexation formula (i.e., for consumers having signed the contract in previous months), and the ones based on the new indexation formula (i.e., for new consumers). Further note that we do not know which price each consumer pays, as we only observe the new tariff sheet each month.

Because consumers under fixed-price contracts are insulated from price fluctuations for the duration of their contract, this feature must be accounted for when constructing a coherent price

[3] Each year, the CREG performs a study comparing the European electricity and natural gas prices for residential, small professionals, and large industrial consumers.
[4] Example of indexation formula: Price = Mark-up + (Coeff x Index variable). The Mark-up, Coeff, and choice of the Index variable are fixed by the energy providers and valid for the whole duration of the contract. The exact value of the Index variable depends on the wholesale markets.

series. To do so, we distinguish between two price concepts: a marginal price series and an average fixed-price series.

The marginal price series is constructed as the monthly average of all contract tariffs offered to new residential consumers by Engie and Luminus. These tariffs represent prevailing market conditions in each month, and therefore fully incorporate contemporaneous market shocks. As such, the marginal price captures the price signal faced by consumers who enter or renew a contract, and governs marginal consumption decisions.

In contrast, many households are locked into fixed-price contracts signed in earlier periods and therefore face prices that reflect past market conditions. To account for this *contract staggering*[5], we construct an average fixed-price series defined as a rolling twelve-month average of all fixed-price contracts offered by the same suppliers. Because fixed contracts typically have a duration of twelve months, at time t the set of contracts that may still be active includes those offered between $t - 12$ and t. Since we do not observe the exact contract start date or price paid by each household, we proxy the effective fixed price by this simple rolling average.

The effective price faced by households is then constructed as a *weighted average* of the marginal price series and the average fixed-price series. This procedure smooths price shocks over time, reflecting the gradual pass-through of market price changes to consumers as fixed contracts expire and are replaced by new ones. In periods of rapidly changing prices, this mechanism substantially attenuates short-run price variation in the effective price faced by households.

The weights used in this aggregation correspond to the share of households under fixed-price contracts. As this proportion is not directly observed at a monthly frequency, we rely on estimates from the CREG, which reports these shares at several points in time. Prior to the energy crisis, approximately 70% of households were covered by fixed-price contracts (CREG, 2020;2022). During the energy crisis, however, fixed contracts progressively disappeared, and their associated risk premium increased sharply, leading to a substantial decline in coverage. At the peak of the crisis, fewer than 25% of households remained under fixed-price contracts (CREG, 2023).

Because households pay VAT on energy consumption, the VAT-inclusive price is the relevant measure for the price series. During the period under study, the VAT rate for electricity changed several times: it was reduced from 21% to 6% in April 2014, restored to 21% in September 2015, and lowered again to 6% in March 2022 in response to the energy crisis. The VAT rate on gas prices was only reduced once in April 2022. While those latter reductions were initially temporary, the government decided in April 2023 to permanently retain the 6% VAT rate on electricity and gas. Importantly, the latter VAT reduction was introduced in direct response to heightened energy prices, whereas the former VAT change was (plausibly) exogenous[6].

Ideally, the price series would also include distribution and transmission tariffs, as well as other energy-related taxes. Although consumers cannot choose their distribution system operator (DSO)—since allocation is determined solely by geographic boundaries and therefore allows no scope for substitution—incorporating these additional charges is nonetheless important for analyzing consumer behavior. Together, these components represent a substantial share of the

[5] Contracts are "staggered" when contract decisions are taken at different points in time, and these decisions are valid for a certain number of periods

[6] For an analysis of the impact of the VAT reduction on electricity prices during 2014-2015, see Hindriks and Serse (2022)

total energy price faced by households and directly affect consumption decisions by shaping household budget constraints.

However, these tariff components are fully observed only for a limited subset of DSOs over the entire study period, or for all DSOs only from 2019 onward. Given the data constraints on consumption discussed below, retaining the full sample period is therefore preferable; consequently, these components are excluded from the estimation dataset. This omission is expected to affect only the precise magnitude of the estimated price elasticity, without altering the substantive conclusions of the analysis. Because distribution, transmission, and energy-related taxes exhibit relatively little month-to-month variation, their inclusion would dampen overall price volatility and thus tend to yield elasticity estimates of larger absolute magnitude.

Figure 1 and 2 displays the VAT-inclusive price series of households for electricity and gas, respectively, in Belgium's three regions, Wallonia, Flanders, and Brussels. Prices rose sharply after 2022. This was initially driven by the post Covid recovery when demand surged, while supply chains remained constrained. It was further exacerbated by the Russian invasion of Ukraine (in February 2022), which pushed prices well above historical levels. Regional price disparities can be explained by two different factors. First, in principle, energy providers can set different prices across regions, as tariff schedules are defined at the regional level. In practice, however, particularly for large energy providers, such price differences are small and infrequent. Notably, within a given region, electricity prices should be identical even when served by different DSOs. Second, for electricity, regional price differences can be attributed to green certificate schemes, whose rates vary across regions, and to cogeneration fees, which are specific to Flanders.

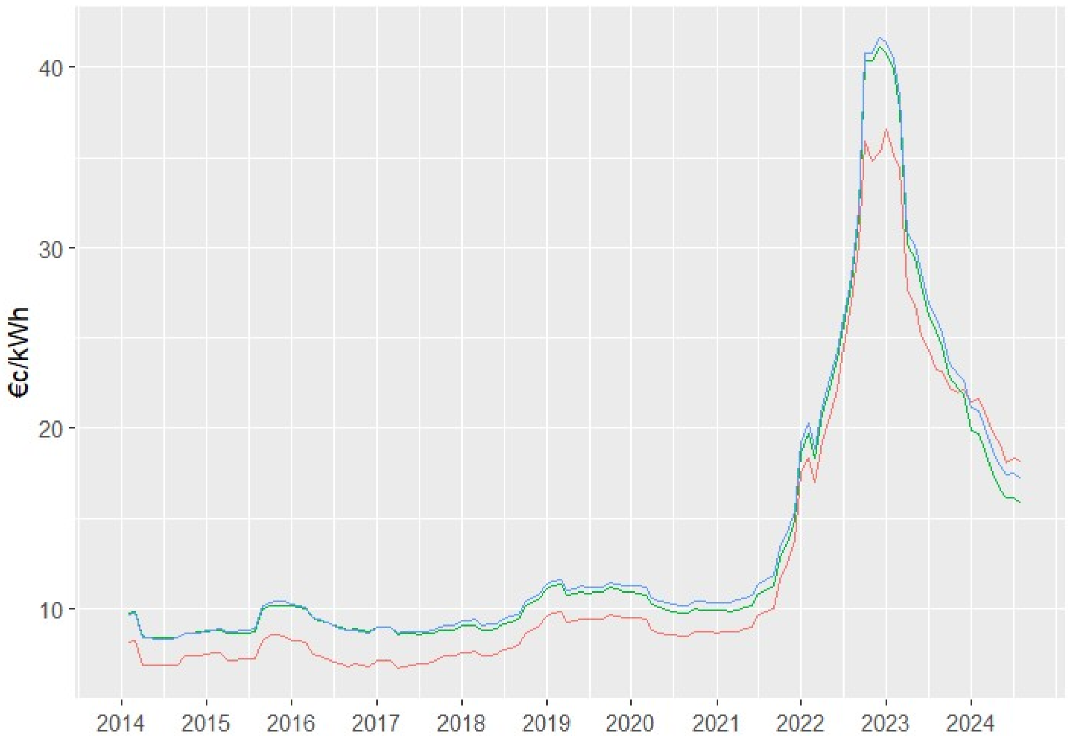

FIGURE 1: Residential Regional Electricity prices

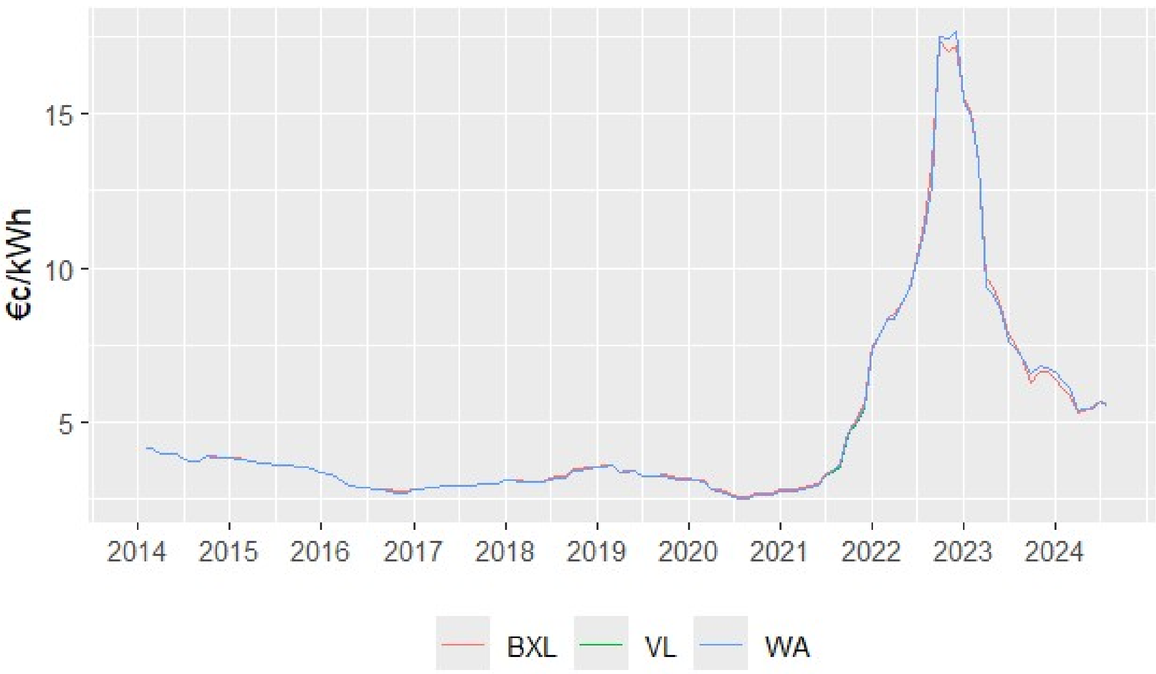

FIGURE 2: Residential Regional Gas prices

The monthly *aggregated* volumes of gas and electricity transmitted through each DSO are provided by Synergrid, the federation of energy network operators in Belgium. This data is broken down into the residential and non-residential sectors. With 21 DSOs, this yields a total of 42 consumption time series. The reported figures measure only consumption drawn from the distribution grid. This distinction is particularly important in the case of electricity, as part of the demand may be met through household self-generation from photovoltaic panels.

The reported volumes combine real metering readings with estimates at individual market points. In practice, real consumption is established after three years (37 months), coinciding with the completion of the financial settlement process. At present, real consumption is available up to April 2020; beyond this date, the reported consumption is a mix of actual and estimated values.

This presents a methodological challenge, as the periods encompassing the COVID-19 pandemic and the subsequent energy crisis are characterized by atypical consumption patterns. The absence of real consumption data for these periods introduces a risk of bias. Although the precise estimation methods employed are not accessible, it is reasonable to expect that household consumption increased during the pandemic. Conversely, during the (unexpected) energy crisis, the price peak likely led to a contraction of overall consumption.

Figures 3 and 4 illustrate the evolution of monthly aggregated electricity and gas consumption for households connected to the distribution grid. A notable feature in Figure 3 is the decline in household consumption during summer months—typically periods of lower demand—up to the summer of 2020. However, beginning in June 2021, coinciding with the end of the COVID-19 restrictions and the onset of rising energy prices, summer consumption increased relative to the previous year. This trend became even more pronounced in the summer of 2022, when electricity prices reached historic high levels. Several factors may account for this pattern. One possibility is the influence of weather conditions, which can elevate energy demand during atypically cool or hot summers. A second explanation is that a considerable share of households was effectively insulated from the surge in electricity costs because they were paying contractually fixed rates that remained below the prevailing market price. As a result, these households had not yet experienced the full impact of the energy crisis shock. Alternatively, the methodology used to estimate consumption for these months—rather than relying exclusively on observed data—may not fully capture behavioral responses during the energy crisis, potentially introducing distortions. This constitutes a notable limitation of the dataset that we will correct as soon as possible with data updating.

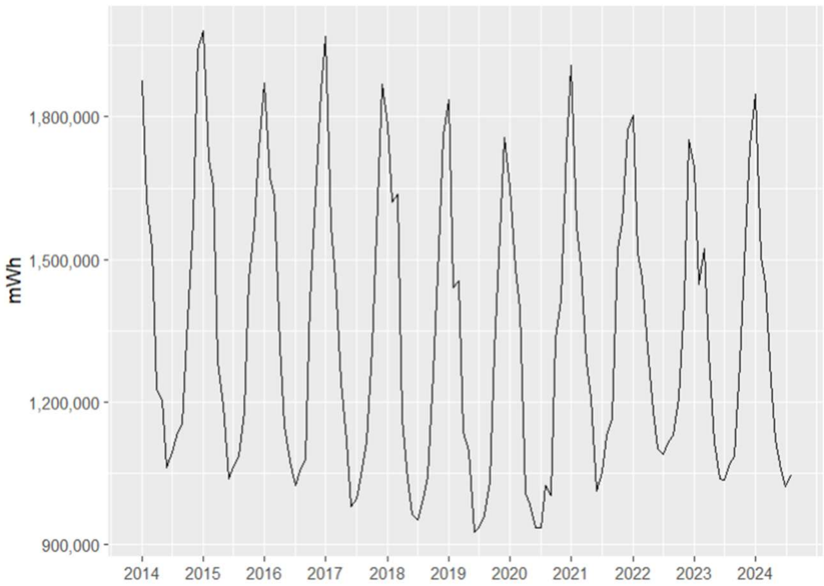

FIGURE 3: Belgium's Residential Electricity Consumption

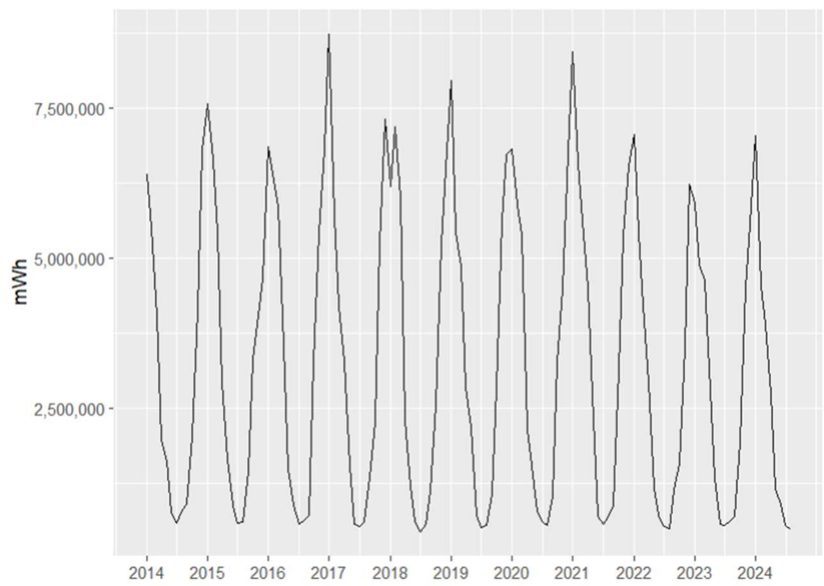

FIGURE 4: Belgium's Residential Gas Consumption

In addition to energy consumption and price data, we incorporate meteorological data from the International Energy Agency to control seasonal fluctuations in electricity and gas demand. Variables such as monthly average temperature, solar radiation, and humidity index are included to capture the influence of weather on energy consumption. However, one important limitation is the inability to identify which consumers benefit from the social tariff. As such, we cannot isolate the consumption behavior of this low-income group, which may be subject to different price sensitivity because they benefit from lower prices.

Table 1 reports summary statistics for electricity and gas average monthly consumption, residential electricity and gas prices, and meteorological conditions before and after the energy crisis (after July 2021). The data indicate that average energy consumption declined during the energy crisis. While this reduction may be explained by the sharp increase in energy prices, it may also be attributed to more favorable meteorological conditions during the period, suggesting that the decrease cannot be attributed solely to price effects.

	Before Energy Crisis January 2014-june 2021		**During Energy Crisis July 2021-august 2024**	
	Average	**Standard-deviation**	**Average**	**Standard-deviation**
Average Residential Electricity Consumption (kWh)	287.54	76.51	275.84	62.30
Average Residential Gas Consumption (kWh)	1215.88	893.54	979.89	1276.32
Residential Electricity Prices (€c/kWh)	9.57	1.00	23.87	8.76
Residential Gas Price (€c/kWh)	3.22	0.41	8.49	3.89
Daylight	736.866	173.17	744.86	173.65
Temperature	11.05	5.39	12.04	5.32
Humidity Index	11.43	7.10	12.85	7.05

Table 1: Monthly Averages and Standard-Deviation Before and During the Energy Crisis

The comparison of standard deviations highlights a pronounced asymmetry between gas and electricity markets. Both markets face a similar sharp rise in price volatility (price volatility, measured by the standard deviation, rose from 1 to 8.76). However, electricity demand remains largely unresponsive; the standard deviation of residential electricity consumption declined modestly, from 76.51 to 62.30. Residential gas demand exhibited a markedly different response. Gas consumption volatility (measured by the SD) increased substantially (893.54 → 1276.32) amid a sharp rise in price volatility (0.41 → 3.89), suggesting that residential gas demand is more sensitive to price fluctuations. These variability measures are largely driven by the crisis period, during which volatility was extreme, making pre-crisis price fluctuations relatively negligible in the full sample. Meteorological data, by contrast, exhibits remarkably similar variability before and during the crisis.

3. Methodology

To assess the responsiveness of energy consumption to large price changes, we estimate three alternative econometric specifications. We begin with a standard *constant-elasticity* model, i.e., a model where the price-elasticity of demand does not vary with the price or consumption level.

$$Q = AP^{-\varepsilon}$$

Where *Q* is demand, *A* is a scaling parameter, *P* is price, and *ε* is (constant) price elasticity of demand. We show that the model yields an unexpectedly low elasticity. We try two additional nonlinear specifications: a *structural break* model at the onset of the energy crisis and an *optimal threshold* model that allows for threshold effects in the price variable. These models permit price elasticities to differ between periods of low and high energy prices. Each specification is estimated separately for the residential sector in each market.

Iso-elastic demand models are widely used in electricity and natural gas demand estimation because of their analytical convenience and empirical tractability. Log–log specifications produce coefficients that are directly interpretable as price elasticities and can be readily estimated using standard econometric techniques. The baseline model is given by the following equation:

$$\ln(C_{it}) = \alpha + \beta \ln(P_{it}) + \gamma' \ln(X_t) + \mu_i + \tau_t + \varepsilon_{it}$$

where C_{it} denotes average consumption per grid connection, i.e., EAN in DSO i during month t, P_{it} is the corresponding electricity price as constructed in the previous section, and X_t includes meteorological variables, the number of grid connections, and— in the non-residential specification—auto-produced electricity. Monthly fixed effects τ_t are included to flexibly capture common seasonal patterns in electricity demand.

The term μ_i denotes DSO fixed effects, which control for time-invariant heterogeneity across distribution system operators, such as differences in customer composition, network characteristics, urbanization, and persistent micro climatic conditions. While the energy component of electricity prices is common across DSOs within the same region, network tariffs are DSO-specific and depend on factors such as network topology, infrastructure density, and historical investment decisions. Detailed data on network charges at the DSO level are not available in our dataset. These persistent differences affect both the level of electricity consumption and the effective price faced by consumers. Failing to account for them could therefore bias the estimated price elasticity. By including DSO fixed effects, we absorb time-invariant heterogeneity related to network cost structures and other persistent DSO characteristics. The identification of β relies on within-DSO variation over time, isolating the response of consumption to price changes net of persistent cross-sectional differences, such as network charges. The coefficient β can therefore be interpreted as the short-run price elasticity of grid electricity or gas demand.

For the estimated elasticity to be consistent, prices must be strictly exogenous to unobserved demand shocks, meaning that the idiosyncratic error term is uncorrelated with past, current, and future price realizations within each DSO, i.e., $E[\varepsilon_{it} \mid P_{i_1}, \ldots, P_{it}, \mu_i] = 0$. Violation of this assumption would lead to endogeneity bias, potentially distorting the elasticity estimates. Weather variables are included in the model to mitigate this risk, as in the short-run, they are the major determinants of energy consumption patterns, which in turn can affect market prices.

We expect that higher average monthly temperatures are generally associated with lower gas and electricity consumption during the heating season. Conversely, lower temperatures tend to increase heating requirements, particularly for gas. Solar radiation, by increasing passive heating and daylight availability, is expected to reduce heating and lighting demand, thereby lowering both gas and electricity consumption. Humidity may influence energy demand, as higher levels in cold months can intensify the feeling of cold and increase heating requirements, while in milder conditions, its effect may be minimal or reversed.

A constant elasticity specification assumes that the proportional consumption response to price change is independent of the price level. This serves as a parsimonious approximation to an otherwise potentially complex and unknown demand relationship. The estimated elasticity should therefore be seen as the constant proportional response that best fits data over the range of price variation in the data, rather than as a structural property of the underlying demand function.

Suppose that the true relationship between consumption C and prices P is given by a positive, differentiable function $C = f(P)$, whose elasticity

$$\varepsilon(P) = \frac{d\ln\, f(P)}{d\ln\, P}$$

may vary with the price level. Taking logarithms yields $\ln\, C = \ln\, f(P)$, which in general is a nonlinear function of $\ln P$. Estimating a log–log model amounts to approximating this unknown function by a linear function of $\ln P$ over the range of the observed data.

From this perspective, the estimated coefficient β should be interpreted as the single constant elasticity that provides the best global approximation to the true relationship in a least-squares sense. Specifically, β corresponds to the slope of the straight line that best fits the log-transformed relationship between consumption and prices. When the true elasticity varies with P, the log–log specification replaces this varying elasticity with a constant value that reflects an average proportional response over the observed range of prices, with greater influence from regions of the data that are more informative for identifying price responsiveness.

Consequently, the use of a constant-elasticity model is not intended to impose a restrictive assumption on the true data-generating process. Instead, it provides a convenient and interpretable approximation that captures the dominant proportional relationship between consumption and prices across the sample[7]. Only in the special case where the true elasticity is constant does the log–log model coincide exactly with the underlying demand function.

We develop two additional price-specific regime models to account for the distinct dynamics observed during periods of low and high energy prices: a structural break model where the break is set at the start of the energy crisis, and a threshold model with energy prices used as the threshold variable. The energy crisis period is characterized by a sharp and persistent increase in

[7] In Appendix A, we also test a linear model as an alternative demand specification to the iso-elastic demand, i.e., the constant elasticity model. Note that similarly, the linear specification can be interpreted as a local approximation that summarizes the average marginal effect of prices on consumption over the observed price range. While the linear model implies price elasticities that vary with the level of prices and consumption, the log–log model imposes a constant elasticity. Both models highlight different aspects of the price–consumption relationship.

energy prices, which may alter consumption behavior differently. Our central hypothesis is that agents respond asymmetrically to price changes once prices reach some pivotal levels.

High salient price increases may induce stronger conservation responses, leading households to reduce energy consumption more aggressively. However, beyond a certain price threshold, further reductions become increasingly difficult, as energy use approaches subsistence levels. These dynamics motivate the use of regime-specific models that allow the price–consumption relationship to vary between low- and high-price periods.

An additional motivation for introducing these models is the pronounced heterogeneity in volatility across price regimes. Energy prices show substantially higher price variance during the crisis period compared to earlier periods. Meanwhile, household electricity consumption volatility declines, whereas residential gas consumption volatility rises. Failing to account for this regime-dependent heteroskedasticity may lead to inefficient estimation (and misleading inference). Furthermore, the divergence in price and consumption volatility across regimes indicates a potential structural shift in the relationship between prices and demand, motivating the use of models with regime-dependent elasticities. The structural break model is designed to capture changes in consumption-price relationships that occur after a specific point in time when an exogenous event fundamentally alters the economic environment. Formally, the model can be expressed as:

$$\ln(C_{it}) = \alpha \quad + \beta_L \ln(P_{it}) \times D_{pre} + \beta_H \ln(P_{it}) \times D_{post} + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

Where D_{pre} and D_{post} are binary indicator variables that take the value 1 in the period before and after the break, respectively, and 0 otherwise. The intercept term α captures the baseline level of log consumption. The coefficients β_L and β_H represents the price elasticity of demand before and after the structural break, enabling a direct comparison of consumer responsiveness across regimes. Note that the control variables, X, are the same as in the iso-elasticity model. The only difference between the two sub-regimes is the price variable. All other parameters are the same across regimes.

Conditional on the exogenous break date, the structural change model is estimated by ordinary least squares. Under the assumption that the regressors are strictly exogenous with respect to the error term, the OLS estimator is consistent for the regime-specific parameters. Because the break date is exogenous rather than estimated, the analysis abstracts from break-date uncertainty. Consequently, the results should be interpreted as conditional on the validity, i.e., the exogeneity, of the break date assumption.

An additional and important identifying assumption is that prices are exogenous to demand. This assumption may be too restrictive in settings where prices and quantities are jointly determined. If prices respond endogenously to demand conditions, the estimated coefficients may reflect both demand behavior and price-setting mechanisms. The empirical results should therefore be interpreted with caution and viewed as conditional on the assumption of price exogeneity.

We interpret the energy crisis as a plausible and largely exogenous structural break for households, as it was driven by forces operating far outside the sphere of influence of households. The crisis was associated with an unusually large, salient, and persistent increase in electricity prices, accompanied by broader macroeconomic repercussions—including a sharp rise in headline inflation—and substantial changes in retail electricity contract structures. In Belgium, this period coincided with a pronounced shift from fixed-price toward variable-price contracts, mechanically increasing households' exposure to wholesale price fluctuations. While the energy crisis did not originate from a single event, it resulted from a sequence of global and geopolitical shocks beginning in mid-2021, including the post-COVID worldwide demand rebound, tightening conditions in global LNG markets, weather-related supply constraints in Europe, the progressive reduction of Russian gas deliveries in late 2021, and ultimately the Russian invasion of Ukraine in early 2022. Crucially, these developments were driven by global supply conditions, international energy markets, and geopolitical dynamics, and were not caused by, nor responsive to, the consumption decisions of Belgian households. From their perspective, the resulting price increase therefore constitutes an unexpected and externally imposed shock. Although a number of policy measures—such as VAT reductions, extensions of social tariffs, and lump-sum energy transfers—were introduced endogenously in response to rising prices, these interventions occurred after the initial surge and do not invalidate the exogeneity of the underlying shock itself. Given the gradual accumulation of these global factors, the precise dating of the break is necessarily imperfect. We assume July 2021 as the baseline break date, corresponding to the onset of sustained price increases in wholesale energy markets. To mitigate concerns regarding timing and remaining endogeneity, we perform sensitivity analyses in section 5, including multiple placebo break tests.

To capture regime-specific response depending on the price levels directly, we also develop a threshold regression model for non-dynamic panels, inspired by Hansen (1999).[8] The model allows for the consumption-price relationship to change once a threshold variable crosses an unknown critical value. In the context of energy demand, this approach is particularly useful for capturing nonlinearities in price elasticity that may shift when prices exceed a certain level. It is important to note that the threshold level is not predetermined but rather estimated endogenously from the data. Formally, the model partitions the sample into two regimes based on whether the threshold variable—here, the price—exceeds a parameter θ. The model can be expressed as:

$$\ln(C_{it}) = \begin{cases} \alpha \quad + \beta_L \ln(P_{it}) + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it}, & if\ P_{it} \leq \theta \\ \alpha \quad + \beta_H \ln(P_{it}) + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it}, & if\ P_{it} > \theta \end{cases}$$

where θ is the unknown threshold parameter, β_L is the price-elasticity when prices are below or equal to the threshold, β_H is the price-elasticity when prices are above the threshold, α is constant which capture the average consumption across price regimes. All other parameters are the same as in the baseline model. Note that, contrary to the specification in Hansen (1999), we only assume that the price slope changes around the threshold. All other coefficients, including the DSO fixed effects, are kept constant across regimes.

In addition to the standard ordinary least squares assumptions, estimating the model requires that both the threshold-dependent regressors and the threshold variable vary over time. Estimation proceeds by searching over a finite set of distinct candidates for the threshold given by the data. At most, the set contains n*T values. To avoid an extreme split with too few observations in one regime, a trimmed range of observed values for the threshold variable is considered. This is done by dropping 10% of the smallest and highest values of the set of potential candidates. The remaining set constitutes the search grid for θ. For each candidate θ, the parameters of the model are estimated by ordinary least squares on the two regimes - with all coefficients staying constant across regime except for the price coefficient-, and the residual sum of squares (SSR) is computed. The estimated threshold θ is the value that minimizes the SSR,

[8] We thank Vincent Bodart for suggesting using this alternative specification.

which provides the best fit for the data. As a result, the slope coefficient is a function of θ. Once $\widehat{\theta}$ is found, the optimal slope coefficient estimate is given by $\widehat{\beta} = \beta\ (\widehat{\theta}\ )$.

$$\widehat{\theta} \quad = argmin\ SSR(\theta)$$

The threshold model and the structural break model are conceptually related, as both frameworks aim to capture regime changes within a data-generating process. However, they differ in how the location of the regime change—or breakpoint—is determined. In the structural break model, the breakpoint is assumed to occur at a specific point in time, typically associated with an external event, here the energy crisis. In contrast, the threshold model assumes that the regime shift is driven endogenously by the value of a particular threshold variable. When this variable crosses a certain critical value, the behavior of the system changes, thereby indicating a transition from one regime to another.

Despite these differences, both approaches rely on a set of similar underlying assumptions to ensure the validity of their results. First and foremost, both models require the exogeneity of the breakpoint, meaning that the structural change—whether caused by an external event or a threshold crossing—must not be correlated with the error term of the model. This ensures that the estimated break reflects a genuine structural change rather than spurious correlation or omitted variable bias. Another key requirement is that there must be a sufficient number of observations within each regime to allow for reliable estimation and statistical inference.

4. Analysis:

Tables 2 and 3 report the estimated coefficients for the residential electricity and gas demand models respectively. Results for the non-residential sector are presented in Appendix C. The reported coefficients can be interpreted as elasticities, representing the average percentage change in energy consumption associated with a one percent increase in the explanatory variables.

The constant term captures baseline energy consumption net of DSO and monthly fixed effects and does not have a direct economic interpretation. The difference in the magnitude and statistical significance of the constant term across specifications only reflects changes in model structure, rather than substantive shifts in baseline consumption.

Across all specifications and for both markets, the estimated coefficients on the control variables generally exhibit the expected signs and are statistically significant. Higher temperatures are associated with a reduction in electricity/gas consumption. The humidity index is positively correlated with electricity/gas demand. In addition, longer daylight duration is associated with lower electricity/gas consumption on average, reflecting reduced lighting needs.

The estimated effects of the control variables are of similar magnitude across specifications, indicating that the results are robust to alternative model specifications. This consistency indicates that the main conclusions regarding the relationship between electricity consumption and the control variables do not depend on the specific specification adopted.

Residential Electricity			
	Dependent variable:		
		Consumption	
	Const. Elast. Model	Struct. Break Model	Threshold Model
Price	-0.032***		
	(0.003)		
Price Regime			
Low Price		-0.159***	-0.094***
		(0.009)	(0.009)
High Price		-0.117***	-0.069***
		(0.006)	(0.006)
Temperature	-0.166***	-0.162***	-0.177***
	(0.009)	(0.010)	(0.010)
Daylight	-3.162**	-1.559	-5.271***
	(1.364)	(1.302)	(1.426)
Humidity Index	0.020***	0.020***	0.021***
	(0.001)	(0.001)	(0.002)
Constant	27.386***	16.795*	41.825***
	(9.234)	(8.810)	(9.656)
DSO Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Observations	2,659	2,659	2,540
R2	0.897	0.904	0.898
Adjusted R2	0.895	0.903	0.897
Residual Std. Error	0.081 (df = 2623)	0.078 (df = 2622)	0.081 (df = 2504)
F Statistic	650.499*** (df = 35; 2623)	687.493*** (df = 36; 2622)	630.900*** (df = 35; 2504)
Note:			*p<0.1; **p<0.05; ***p<0.01
			Standard errors are clustered at the unit (DSO) level.

TABLE 2: Residential Electricity Models

Most DSO effects and monthly fixed effects are statistically significant. Their inclusion helps account for unobserved heterogeneity across distribution system operators and seasonal patterns in electricity consumption, thereby stabilizing the estimated coefficients. The inclusion of these fixed effects also substantially increases the explanatory power of the models, as reflected in the high R^2 values, which are around 0.90 for the electricity market and up to 0.97 for the gas market, across all specifications. Although these values may appear unusually high, they are explained by the rich set of regressors and fixed effects included in the models – 38 regressors in the constant elasticity model. Further note that our primary interest lies in the identification of price elasticities rather than in maximizing the explanatory power of the models. Accordingly, the high R^2 values should be interpreted with caution. Moreover, the resulting R^2 levels are consistent with those reported by Hindriks and Serse (2022), who employ a similar empirical approach using comparable data. However, their limited sample period (January 2013–December 2016) does not feature any price movements of a magnitude comparable to the pronounced increase captured in our post-July 2021 data. The first two specifications are estimated on the same sample, comprising 2,659 observations for the electricity market and 2,026 for the gas market. In the threshold specification, the bootstrap procedure requires a balanced panel; therefore, DSOs with incomplete time series are excluded. This results in the exclusion of PBE and AIEG in the residential sector, reducing the sample to 2,540 observations. The gas data was already balanced. The reduction in sample size is driven solely by data availability constraints.

Residential Gas

	Dependent variable:		
		Consumption	
	Const. Elast. Model	Struct. Break Model	Threshold Model
Price	-0.159***		
	(0.006)		
Price Regime			
Low Price		-0.038	0.032
		(0.028)	(0.023)
High Price		-0.102***	-0.059***
		(0.014)	(0.010)
Temperature	-0.613***	-0.612***	-0.613***
	(0.039)	(0.038)	(0.039)
Daylight	-9.317***	-9.648***	-7.907**
	(3.213)	(3.090)	(3.294)
Humidity Index	0.068***	0.068***	0.067***
	(0.005)	(0.005)	(0.005)
Constant	70.126***	72.240***	60.376***
	(21.714)	(20.899)	(22.284)
DSO Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Observations	2,026	2,026	2,026
R2	0.972	0.973	0.972
Adjusted R2	0.972	0.972	0.972
Residual Std. Error	0.160 (df = 1995)	0.159 (df = 1994)	0.160 (df = 1994)
F Statistic	2,331.965*** (df = 30; 1995)	2,297.816*** (df = 31; 1994)	2,258.668*** (df = 31; 1994)
Note:			*p<0.1; **p<0.05; ***p<0.01
			Standard errors are clustered at the unit (DSO) level.

TABLE 3: Residential Gas Models

Under the constant elasticity specification, the estimated price elasticity is −0.032 for the electricity market and −0.159 for the gas market. These estimates imply that on average a 1% increase in electricity prices reduces grid electricity consumption by approximately 0.032% and gas consumption by 0.159%. While both elasticities are statistically significant, the magnitude for the residential electricity is relatively small.

This value is particularly low compared to existing evidence from the empirical literature on energy demand. For example, Labandeira et al. (2016) reports an average short-run elasticity of approximately −0.21 for electricity demand, and Espey and Espey (2004) find a mean short-run residential electricity elasticity around −0.35. A more recent systematic review focused on electricity demand report average short-run elasticities on aggregated data of −0.41 (Mubiinzi *et al.,* 2024).

In the presence of large and highly salient price increases, one might have expected energy consumption to respond more strongly. This highlights the limitations of the constant elasticity model such as assuming the same proportional consumption response to both a 10% and a 100% price increase. Our two alternative regime specifications allow to capture regime specific price elasticities.

A first observation from the results tables is that the structural break model (Model 2) and the threshold model (Model 3) produce different estimates. This difference arises from the way the two models partition the sample across regimes. In the structural break model, observations are divided according to time, that is, into periods before and after the exogenously identified break date. By contrast, the threshold model partitions observations based on whether prices lie above or below a given threshold. Note that while the break point in the structural break model is explicitly determined, the threshold value in the threshold model is endogenously estimated within the model.

Figures 5 and 6 illustrate how monthly average prices are allocated across regimes under the two models. Observations in the upper-left quadrant are assigned to the high-price regime under the threshold model but to the low-price or pre-break regime under the structural break model, while the opposite classification applies to observations in the lower-right quadrant. This comparison illustrates that the two approaches capture price regimes using distinct classification rules and helps explain why estimated elasticities differ across specifications.

By partitioning the sample differently, the two models also capture different effects: a price level effect and a crisis effect. While both the threshold and structural break models estimate marginal price elasticities, the former captures nonlinear responses associated with the price level, whereas the latter reflects changes in overall responsiveness driven by structural changes following the energy crisis.

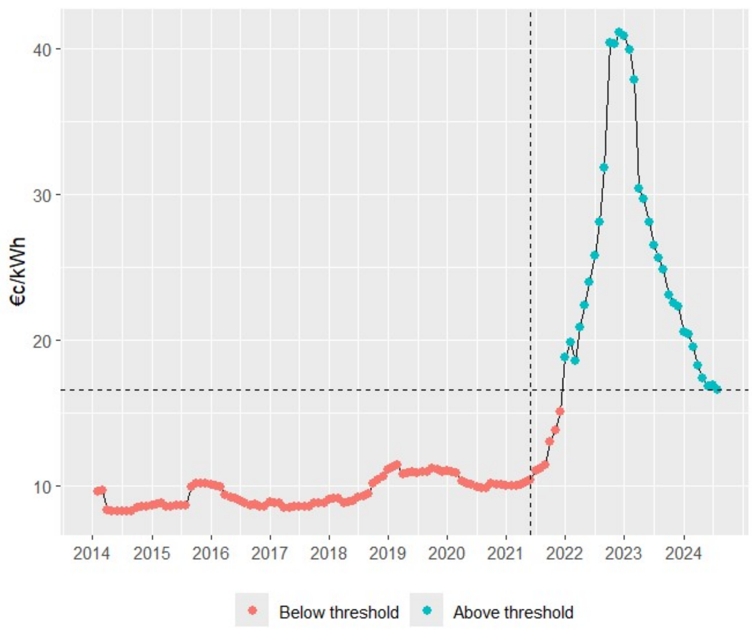

FIGURE 5: Electricity Price Regime Classification: Structural Break versus Threshold Models

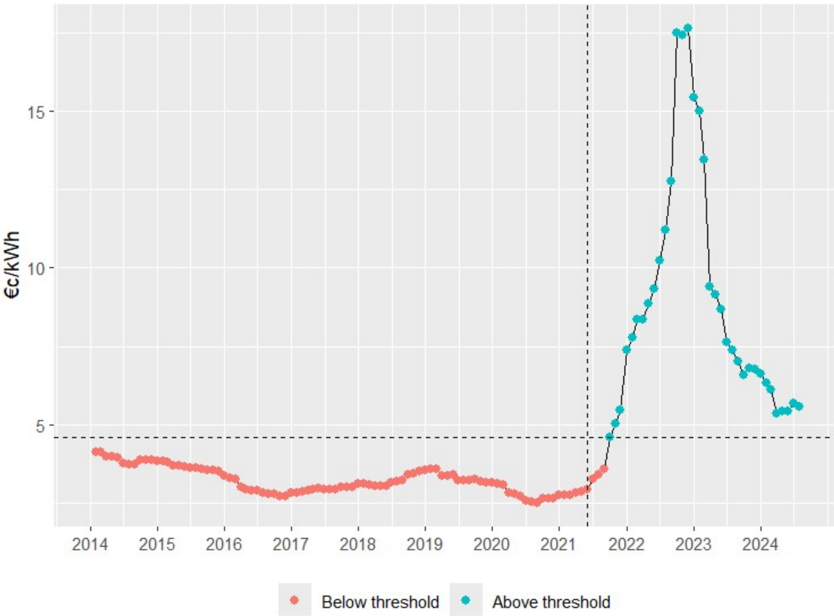

FIGURE 6: Gas Price Regime Classification: Structural Break versus Threshold Models

The regime-based models reveal lower price elasticity in high-price regimes than in low-price regimes in the electricity market. In contrast, for the gas market, price elasticity is statistically significant only during high-price periods. For electricity, the regime-specific estimates indicate that price elasticities range from −0.159 (model 2) to −0.094 (model 3) in the low-price regime, and from −0.117 (model 2) to −0.069 (model 3) in the high-price regime, depending on the model specification. All estimated elasticities are statistically significant at the 1% level. The elasticities observed in the low-price regime, particularly those derived from the structural break model, are consistent with the findings of Hindriks and Serse (2022), who report residential price elasticities ranging from −0.09 to −0.17 over a similar period. Turning to the gas market, the results differ across regimes. During high-price periods, the estimated elasticities are −0.102 (model 2) and −0.059 (model 3), both statistically significant. However, in the low-price regime, the elasticity estimates are not statistically significant, suggesting limited consumer responsiveness to gas prices when prices are relatively low.

For electricity, the finding that price elasticity remains statistically significant in both regimes but decreases in magnitude in the high-price regime aligns with the evidence in Nawaz et al. (2014). They show that the impact of electricity prices diminishes as the price level increases. However, they find that above a certain threshold, the effect of prices on consumption is statistically insignificant. In our case, the reduction in elasticity observed in the high-price regime is consistent with a gradual attenuation of marginal price effects as prices rise, even though the responsiveness does not disappear entirely. A possible explanation for these results is that even though households reduce their electricity consumption as prices rise, beyond a certain point, once the most accessible and low-effort adjustments have been made, further reductions become increasingly difficult, particularly in the short run. Alternatively, protective mechanisms to the sharp price increase may also explain the reduction in price elasticity between the regimes.

For gas, the absence of statistically significant elasticity in the low-price regime, combined with significant responses during high-price periods, indicates that measurable demand adjustments occur primarily when price levels become sufficiently elevated. This pattern is consistent with the evidence presented by Gabreyohannes (2010). Their results show that price changes have no statistically significant effect on consumption when price changes remain below a certain threshold, whereas sufficiently large increases lead to a significant demand response. Kani (2014) finds that significant reductions in gas consumption only occur when prices exceed a certain threshold, whereas in the low-price regime the estimated price elasticity is positive. Taken together, these findings support the interpretation that demand responses are not only nonlinear but also conditional on the price regime, with statistically significant and negative effects more likely to arise in contexts characterized by sufficiently large price increases.

The relatively low price elasticities observed, particularly during periods of high price regimes, may be explained by the presence of several protective mechanisms. During the energy crisis, the Belgian government implemented measures to mitigate the impact of rising energy prices, including a reduction of the VAT on energy from 21% to 6% and an expansion of eligibility for the social tariff. While the former is accounted for in our analysis, since the price series used is inclusive of VAT, the latter cannot be fully controlled for, as we cannot separate the consumption of the households benefiting from the social tariff from the aggregated consumption. An additional mitigating factor is that a substantial share of households is covered by fixed-price contracts, which shield them from immediate exposure to market price fluctuations. Although our price series is constructed to partially account for this feature, such adjustments remain imperfect and may not fully capture its effects. These protective mechanisms likely dampened the reduction in energy consumption during the crisis. In the presence of rising prices, this would mechanically result in lower estimated price elasticities than would be observed in the absence of such interventions.

Our results may present certain limitations linked to the data and methodological approach. A key identifying assumption underlying the estimated models is the exogeneity of energy prices, that is, prices are assumed to be uncorrelated with unobserved factors that simultaneously affect energy consumption. This simultaneity gives rise to potential endogeneity bias in the estimated price elasticities. For example, in the electricity market, price changes may affect the level of investment in solar panels, which in turn can lead to a reduction in electricity consumption. By not accounting for this indirect channel of consumption adjustment, the estimated price elasticities may be downward biased. Unfortunately, given the limitations of the available data, it is not possible to adequately control for price endogeneity or to instrument electricity and gas prices. The identification strategy we plan in future work is to sample out household with variable contract as treated group and to use the household with fixed contract as control group. We are in the process of requesting those sampling data to the CREG.

Additionally, a share of the consumption data—particularly during the energy crisis period—is estimated rather than real consumption. If these estimates fail to fully capture real behavioral response, consumption variability during high-price periods may be understated, leading to a downward bias in the estimated price elasticity. The data update is on its way and we will adjust our estimates as soon as we receive them.

Finally, differences in estimated elasticities may reflect model misspecification. We therefore assess whether regime-dependent specifications provide a statistically better fit. In the structural break models, we examine whether the relationship between log energy consumption and log prices changes after June 2021 by means of a Wald test[9] at this breakpoint. The null hypothesis tests whether the coefficients associated with the post-break price regime, the high-price regime indicator and the post-break price coefficient, are jointly equal to zero. To test for the presence of a threshold effect we use a bootstrap procedure as suggested by Hansen (1999)[10].

For the residential electricity sector, the linear hypothesis test yields an F-statistic of $F(1, 2622) = 239.46$ (p < 0.001), leading to a clear rejection of the null hypothesis of parameter stability. A similar conclusion holds for the residential natural gas sector, where the Wald test produces an F-statistic of $F(2, 1994) = 18.268$ with a p-value below 0.001. This provides strong evidence of a structural change in the price–consumption relationship after July 2021.

Caution is warranted in interpreting the results of the structural break model. As is well known, Wald- and Chow-type tests rely on a pre-specified breakpoint and may be sensitive to its exogeneity (Hansen, 2001). In the present context, the chosen breakpoint coincides with the onset of a sharp increase in energy prices during the energy crisis and may therefore reflect salient features of the data rather than an exogenous structural change. Moreover, the energy crisis comprises a sequence of overlapping events, making it difficult to pinpoint a single, perfectly exogenous break date. If the true break occurs at a different point within this period, the test may spuriously indicate a structural change due to endogeneity of the breakpoint.

Turning to the threshold model, we test for the presence of a price threshold effect. For the residential electricity sector, the estimated threshold value is $\hat{\theta} = 16.61$. Based on the bootstrap likelihood ratio test, which yields an LR statistic of 201.86 and a bootstrap p-value of 0.169, computed using 1,000 bootstrap replications, we fail to reject the null hypothesis of no threshold effect. The residential gas sector presents similar results. We estimated a threshold of $\hat{\theta} = 4.58$ with an LR statistic of 92.33 and a corresponding p-value of 0.563. Taken together, these results do not allow us to conclude that price levels alone drive heterogeneous price responsiveness.

Although the bootstrap likelihood ratio tests do not provide statistical evidence in favor of a price-based threshold effect, the threshold model remains informative for understanding potential nonlinearities in consumer price responsiveness. First, Hansen (2000) notes that under the null of no threshold effect the threshold parameter is not identified, leading to non-standard asymptotic distributions, and that bootstrap inference is asymptotically valid but depends on sample moments. This implies that finite-sample inference can be fragile, particularly when observations near the threshold are sparse, so failure to reject linearity does not necessarily indicate the absence of heterogeneous behavior. Second, the regime-specific price-elasticity coefficients obtained under the threshold framework remain statistically significant, suggesting that meaningful variation in price responsiveness persists even if the precise location of the threshold cannot be formally established. This indicates that consumers may indeed react differently across price ranges, even if the data does not allow us to pinpoint a sharp structural break. Consequently, the threshold model can still contribute to a richer characterization of demand behavior by highlighting potential nonlinear patterns that a purely linear specification would obscure.

Importantly, however, the inability to statistically favor the threshold specification over the constant elasticity model does not imply that the latter provides an adequate description of

[9] Wald test statistics are based on a heteroskedasticity-robust variance–covariance matrix with standard errors clustered at the DSO level.
[10] The theory behind the inference results are presented in Appendix B.

demand. In the present setting, when the data is not partitioned into distinct price regimes, the low-price regime displays an almost flat trajectory, reflecting very limited price variation under normal market conditions. In contrast, substantial price movements are concentrated in the energy crisis period, during which prices increase sharply and deviate significantly from their typical range.

As a consequence of this uneven distribution of price variation, the estimation of a constant-elasticity model is dominated by observations from the high-price energy crisis period (compressing the price variation in the low-price period). Because prices are comparatively nearly flat during the low-price period, these observations contribute little to the identification of price responsiveness. Instead, the elasticity parameter is primarily identified from the crisis period, where price variation is substantial. By failing to partition the sample into distinct price regimes, the model effectively assigns disproportionate weight to the high-price episode, while consumer responses under normal market conditions are weakly identified.

This imbalance in identifying variation helps explain why constant-elasticity models can yield elasticity estimates that appear unexpectedly low. When the energy crisis period is excluded and the analysis is restricted to the low-price regime, where prices are relatively stable, the resulting elasticity estimates are more plausible and align more closely with those reported in the existing empirical literature.

To clarify this argument, it is useful to restate the meaning of price elasticity in this context. Price elasticity of demand is typically defined as the percentage change in consumption resulting from a one percent change in price. As such, it provides a scale-free measure of the responsiveness of quantity demanded to price changes in the immediate neighborhood of a given price–quantity combination. Formally, the point price elasticity of demand at price p is defined as

$$\varepsilon(p) = \frac{dQ(p)}{dp} \cdot \frac{p}{Q(p)},$$

which expresses demand responsiveness in proportional rather than absolute terms.

This formulation emphasizes that point elasticity is a local property of the demand function. It characterizes responsiveness at a specific point on the demand curve and does not describe responses to large or discrete price changes. By focusing on infinitesimal price variation, point elasticity captures consumer behavior around the observed price level.

When demand is instead estimated using a log–log specification, the model provides a global average of proportional responsiveness. The resulting elasticity is exact only when the true demand function exhibits constant elasticity; otherwise, it constitutes an approximation. Specifically, when the true elasticity varies with price, the log–log coefficient corresponds to the slope of the linear projection of log consumption on log prices and should be interpreted as the constant elasticity that provides the best global approximation, in a least-squares sense, to the true demand function.

The accuracy of this approximation depends on the extent of price variation in the data. When prices vary over a relatively narrow range, the demand function can be well approximated locally by a constant elasticity, and the log–log specification closely captures behavior near the observed prices. In this case, the estimated elasticity provides a reliable summary of price responsiveness and approaches the true point elasticity.

By contrast, when price variation is large or concentrated in specific subperiods, the constant-elasticity assumption becomes a less accurate approximation. The estimated coefficient then reflects an average response over a wide range of prices and may be disproportionately influenced by regions with greater price dispersion. As a result, the log–log model no longer approximates local responsiveness at typical price levels but instead summarizes behavior across heterogeneous price environments.

Much of the empirical literature relies on constant-elasticity models to estimate price responsiveness, often relying on exogenous price shocks to achieve identification. While these shocks are necessary for credible estimation, their presence can introduce substantial variation in prices. When price variation is large, the log–log (constant-elasticity) specification provides a less accurate approximation to the underlying demand function. As a result, the estimated elasticity may not reliably reflect local or typical consumer responses. This issue is particularly relevant in the context of energy economics, where price elasticities are frequently used to assess the impact of environmental policies such as carbon taxes, and over- or underestimation of responsiveness can materially affect policy conclusions.

In sum, while sample partitioning improves the accuracy of elasticity estimation under stable price conditions, the inherent limitations of the log–log model under large or uneven price fluctuations remain. This highlights a fundamental trade-off between model simplicity and the ability to capture heterogeneous, price-dependent demand responses.

5. Sensitivity of the structural break date

In this section, we conduct a series of placebo tests to assess the plausibility of the timing of the structural break and to evaluate whether it can be regarded as externally determined. While no statistical test can formally establish the exogeneity of a break date, here in July 2021, placebo exercises allow us to examine whether the data exhibit patterns consistent with a meaningful and well-identified structural change at that point in time.

The underlying idea is that, if a genuine break occurs in July 2021, alternative break dates in nearby periods should yield weaker evidence of parameter instability. We consider a broad window of alternative break dates spanning July 2020 to July 2022, providing a 24-month interval that includes twelve months on either side of the reference break.

We first examine the absolute difference between the estimated price elasticities before and after the placebo break. A correctly specified break date should maximize this difference, reflecting a sharp change in consumer responsiveness to prices. Second, we assess model fit across candidate break dates using the log-likelihood. The log-likelihood summarizes how well the model explains the observed data, with higher values indicating a better fit. If the break date is correctly specified, allowing for different elasticities before and after that date should improve the model's explanatory power most strongly, leading to a local maximum of the log-likelihood around the true break. Finally, we implement Chow-type structural break tests using a Wald F-statistic that tests the null hypothesis of equality between pre- and post-break elasticities. A correctly identified break date should correspond to the strongest rejection of the no-break hypothesis, that is, to the highest value of the Wald F-statistic. Consistent peaks across these exercises, i.e., elasticity differences, model fit, and Wald test statistics, should provide evidence on whether July 2021 is the most plausible timing of the structural break.

The first three figures present the placebo test results for the residential electricity market. Figure 7 displays the absolute difference between the estimated price elasticities before and after each candidate break date. The largest elasticity discontinuity occurs in October 2021, with only marginal differences relative to adjacent dates. This concentration suggests that the magnitude of the coefficient change is maximized around the selected break period, providing support for the chosen timing. Figure 8 examines model fit across alternative break dates using the log-likelihood. The log-likelihood reaches its maximum in August 2021, with only minor variation in nearby periods. This pattern indicates that allowing for a structural break around this date yields the greatest improvement in the model's explanatory power. Figure 9 reports the Chow-type Wald F-statistic testing equality of pre- and post-break elasticities. The strongest rejection of the no-break hypothesis occurs around the selected break date, reinforcing the evidence from the elasticity differences and the goodness-of-fit criterion. Taken together, these results provide consistent and complementary evidence that the structural break in residential electricity demand is most plausibly located around mid-2021, supporting the validity of the selected break date.

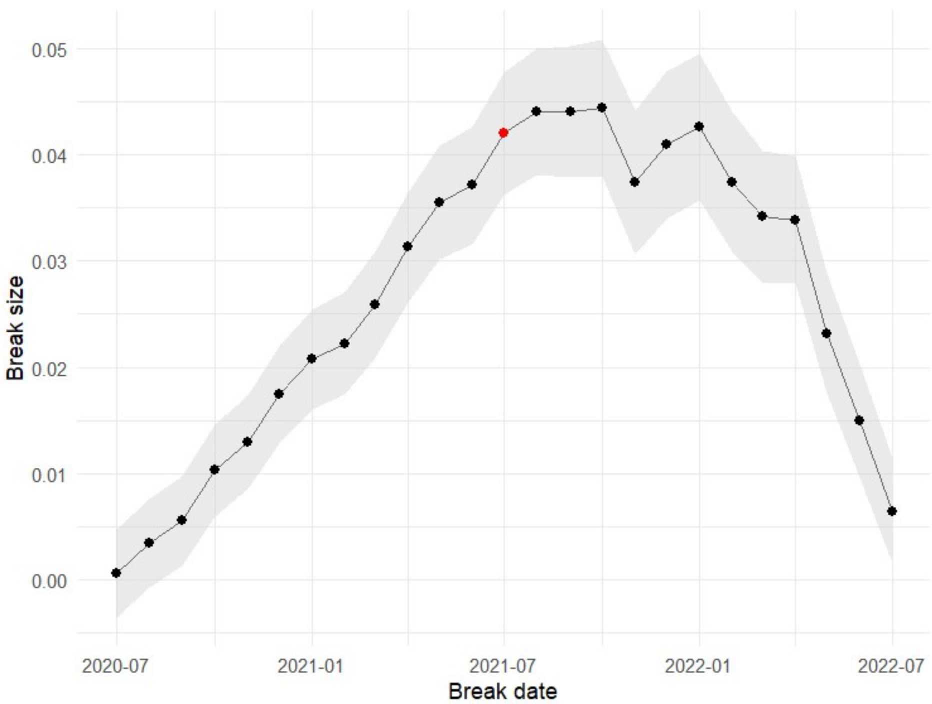

Figure 7: Break Magnitude Difference Across Placebo Dates in the Residential Electricity Market

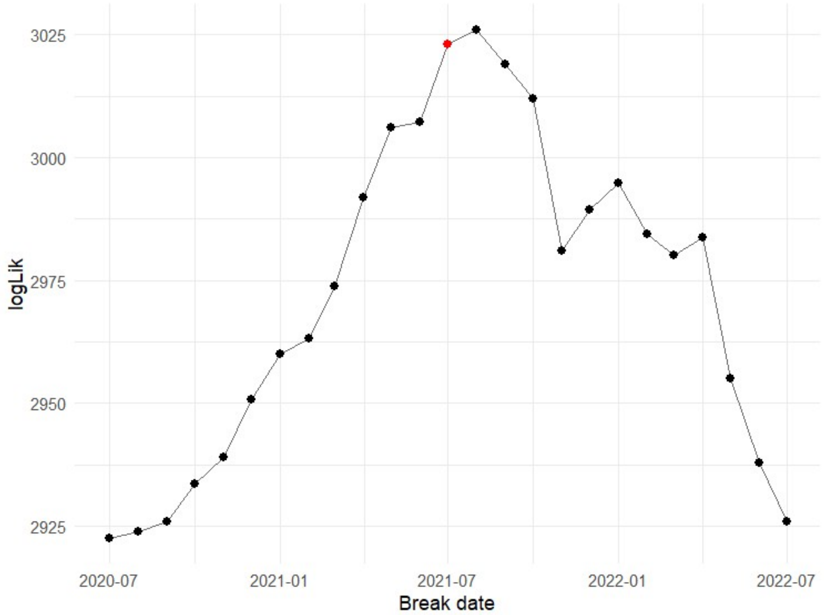

Figure 8: Goodness-of-fit through Log-likelihood Across Placebo Dates in the Residential Electricity Market

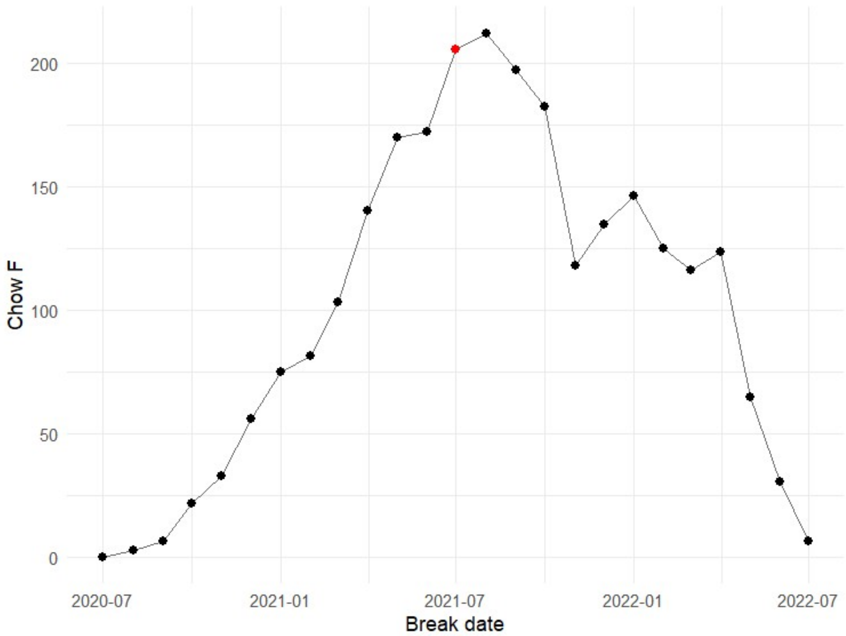

Figure 9: Chow Test Across Placebo Dates in the Residential Electricity Market

Applying the same placebo exercise to the residential gas market yields less clear-cut results. As shown in Figure 10, the absolute difference between pre- and post-break price elasticities reaches its maximum in December 2021, which is several months removed from the selected break date of July 2021. A similar pattern emerges when examining alternative diagnostics: both the goodness-of-fit measure (Figure 11) and the Chow-type Wald F-statistic (Figure 12) attain their maxima in March 2022. Unlike the electricity market, these criteria do not exhibit a clear concentration around a single, well-defined break date.

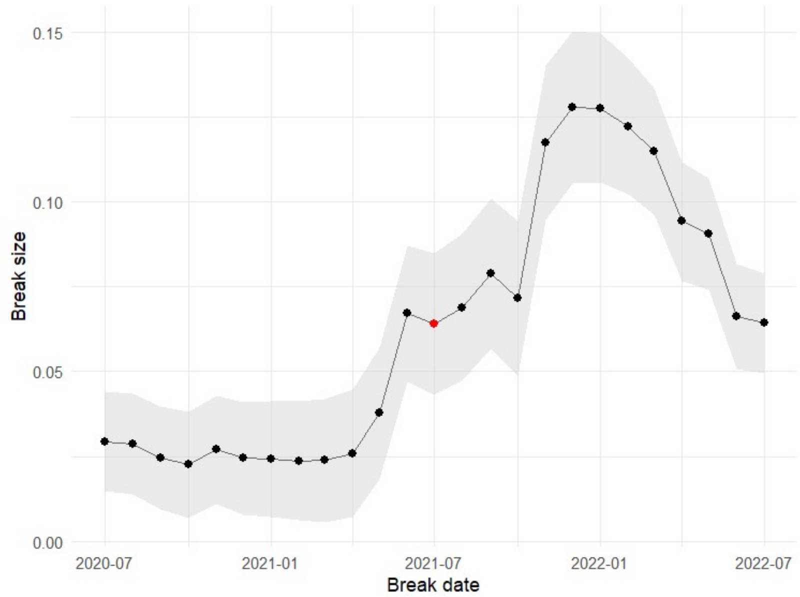

Figure 10: Break Magnitude Difference Across Placebo Dates in the Residential Gas Market

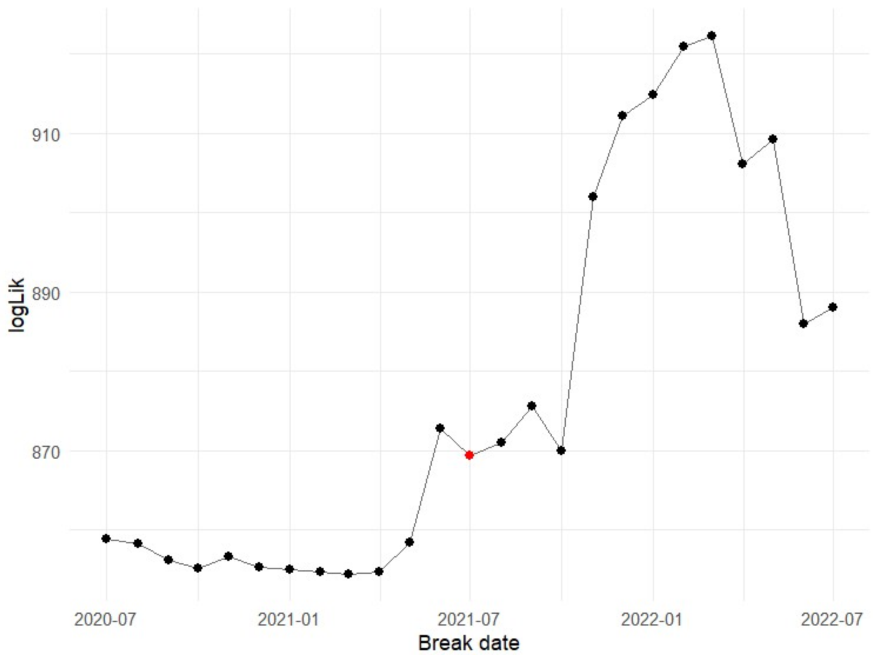

Figure 11: Goodness-of-fit through Log-likelihood Across Placebo Dates in the Residential Gas Market

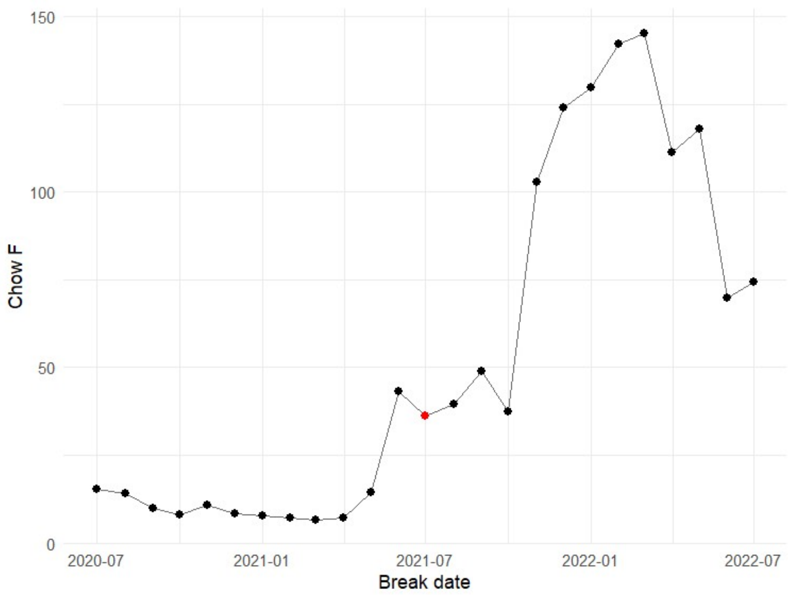

Figure 12: Chow Test Across Placebo Dates in the Residential Gas Market

Taken together, these findings suggest that the timing of structural change in the residential gas market is less sharply identified. The dispersion of peaks across different diagnostics could be consistent with a more gradual adjustment process. In particular, price signals may only affect households progressively as fixed contracts expire and are replaced by variable contracts, delaying the effective pass-through of wholesale price increases[11]. This could generate a gradual change in demand elasticity rather than a discrete shift occurring at a single point in time. Consequently, while there is compelling evidence of a structural break around July 2021 in the residential electricity market, the corresponding evidence for the gas market is weaker and does not support the same degree of confidence in the timing or sharpness of the break.

6. Conclusion

This paper investigates residential energy demand responsiveness in the context of the recent energy crisis, characterized by exceptionally large and highly salient price increases. We estimate price elasticities for residential electricity and gas consumption using three alternative non-linear specifications: a standard constant-elasticity log–log model, a structural break model that captures potential shifts in responsiveness following the crisis, and a threshold model in which price levels endogenously determine regime-dependent elasticities. While the constant-elasticity model corresponds to the conventional approach in the empirical literature, the structural break specification aims to capture broader behavioral changes associated with the crisis period—including salience effects, policy interventions, and other unobserved structural shifts—whereas the threshold model directly tests whether price responsiveness varies with the level of prices.

[11] Although we attempt to account for the gradual replacement of fixed-price contracts by variable-price contracts, this adjustment remains an approximation and may not fully capture the true pace at which contracts are renewed. As a result, the effective pass-through of price changes to households may still occur with a delay that is not entirely reflected in our constructed measure of prices.

A central lesson of this analysis is that the constant-elasticity model may not always provide an appropriate representation of demand behavior in periods characterized by large and uneven price fluctuations. Price elasticity is fundamentally a local concept: it measures responsiveness around a given price–quantity combination. When estimated in a log–log framework, however, the coefficient represents a global least-squares approximation to an underlying demand function that may exhibit price-dependent elasticity. In the presence of substantial price shocks, such as those observed during the energy crisis, the estimated constant elasticity is disproportionately influenced by periods with greater price dispersion. As a result, it may fail to accurately reflect local responsiveness, particularly under stable market conditions. This mechanism helps explain why the constant-elasticity model yields unexpectedly low electricity elasticity in our full-sample estimation.

Alternatively, we show how accounting for nonlinearities and regime-dependent elasticities, especially in the presence of high price increases, can provide meaningful results for evaluating households' energy demand. In the electricity market, consumers adjust their consumption in both low- and high-price regimes, but the magnitude of these adjustments declines as prices rise, revealing a nonlinear attenuation of price effects. This demonstrates that elasticity estimates derived from a single, linear specification would mask meaningful variation in how households respond across different price environments. In contrast, the gas market shows that demand becomes responsive only once prices reach sufficiently high levels, while low-price periods generate no statistically significant behavioral change. This regime-specific sensitivity illustrates an even starker form of nonlinearity: gas demand appears largely inelastic under normal price conditions but becomes elastic when price increases surpass certain thresholds. Taken together, the electricity and gas markets provide two distinct empirical examples of why regime-dependent modeling can be essential, as relying on a single, average elasticity would overlook the very conditions under which price signals meaningfully influence household energy consumption.

Our results must be interpreted considering several limitations. First, data constraints restrict our ability to address potential endogeneity between prices and consumption. The identifying assumption of price exogeneity may be violated if unobserved factors simultaneously affect prices and demand, potentially biasing elasticity estimates. Second, part of the consumption data—particularly during the crisis period—is estimated rather than based on actual metered usage, which may attenuate measured variability and lead to biased elasticities. Third, aggregation issues arise because consumption data include heterogeneous consumer groups, such as households benefiting from social tariffs and those under fixed contract tariffs, while observed price series may not fully reflect effective prices faced by these protected consumers.

Despite these limitations, the analysis contributes to the literature by highlighting the importance of model specification in environments with large price shocks. While constant-elasticity models remain attractive for their simplicity and interpretability, their performance depends critically on the distribution of price variation in the data. In contexts where prices fluctuate within a narrow range, the log–log specification provides a reasonable approximation of local demand behavior. However, when price movements are large, concentrated, or structurally disruptive, regime-dependent models may offer additional insights into heterogeneous responsiveness—even if statistical improvements over the benchmark model are modest.

More broadly, these findings have important implications for policy evaluation and system planning in energy markets. Price elasticities are central not only for assessing the expected effects of instruments such as carbon taxes or tariff reforms, but also for modeling future energy demand—an essential input for ensuring adequate grid maintenance and investment. When elasticity estimates are derived from periods with large exogenous price shocks, the resulting variation can interact with model specification in ways that distort measured responsiveness. Policy simulations based on constant-elasticity assumptions may therefore misrepresent how consumers adjust their consumption. Recognizing the local nature of elasticity and the potential for regime-dependent behavior is crucial for interpreting empirical estimates, particularly during episodes of economic turbulence when price dynamics deviate significantly from historical norms.

References:

Akakpo, K.L., & Barla, P. (2017). The Analysis of Structural Breaks in Gasoline Demand Using a Bayesian Approach.

Alberini, A., Khymych, O., & Ščasný, M. (2020). Responsiveness to energy price changes when salience is high: Residential natural gas demand in Ukraine. *Energy Policy*, *144*, 111534.

Arčabić, V., Gelo, T., Sonora, R. J., & Šimurina, J. (2021). Cointegration of electricity consumption and GDP in the presence of smooth structural changes. *Energy Economics*, *97*, 105196.

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of applied econometrics*, *18*(1), 1-22.

Bessec, M., & Fouquau, J. (2008). The non-linear link between electricity consumption and temperature in Europe: A threshold panel approach. *Energy Economics*, *30*(5), 2705-2721.

Blignaut, J., Inglesi-Lotz, R., & Weideman, J. P. (2015). Sectoral electricity elasticities in South Africa: Before and after the supply crisis of 2008. *South African Journal of Science*, *111*(9-10), 01-07.

Byrne, D. P., Nauze, A. L., & Martin, L. A. (2021). An experimental study of monthly electricity demand (in) elasticity. *The Energy Journal*, *42*(2), 205-222.

Charlier, D., & Kahouli, S. (2019). From residential energy demand to fuel poverty: income-induced non-linearities in the reactions of households to energy price fluctuations. *The Energy Journal*, *40*(2), 101-138.

Commission de Régulation de l'Électricité et du Gaz (CREG). (2023). Composition des portefeuilles de produits par fournisseur et potentiel d'économies pour les particuliers sur le marché belge de l'électricité et du gaz naturel (Étude F2605FR). https://www.creg.be/sites/default/files/assets/Publications/Studies/F2605FR.pdf

Commission de Régulation de l'Électricité et du Gaz (CREG). (2022). Composition des portefeuilles de produits par fournisseur et potentiel d'économies pour les particuliers sur le marché belge de l'électricité et du gaz naturel (Étude F2430FR). https://www.creg.be/sites/default/files/assets/Publications/Studies/F2430FR.pdf

Commission de Régulation de l'Électricité et du Gaz (CREG). (2020). Composition des portefeuilles de produits par fournisseur et potentiel d'économies pour les ménages sur le marché belge de l'énergie (Étude F2165FR). https://www.creg.be/sites/default/files/assets/Publications/Studies/F2165FR.pdf

Espey, J. A., & Espey, M. (2004). Turning on the lights: A meta-analysis of residential electricity demand elasticities. *Journal of Agricultural and Applied Economics*, *36*(1), 65-81.

Fouquau, J., Destais, G., & Hurlin, C. (2009). Energy demand models: a threshold panel specification of the 'Kuznets curve'. *Applied Economics Letters*, *16*(12), 1241-1244.

Gabreyohannes, E. (2010). A nonlinear approach to modelling the residential electricity consumption in Ethiopia. *Energy Economics*, *32*(3), 515-523.

Gao, J., Peng, B., & Smyth, R. (2021). On income and price elasticities for energy demand: A panel data study. *Energy Economics*, *96*, 105168.

Hansen, B. E. (1996). Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica: Journal of the econometric society*, 413-430.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of econometrics*, *93*(2), 345-368.

Hansen, B. E. (2001). The new econometrics of structural change: Dating breaks in US labor productivity. *Journal of Economic perspectives*, *15*(4), 117-128.

Hindriks, J., & Serse, V. (2022). The incidence of VAT reforms in electricity markets: Evidence from Belgium. *International journal of industrial organization*, *80*, 102809.

Ito, K., Ida, T., & Tanaka, M. (2018). Moral suasion and economic incentives: Field experimental evidence from energy demand. *American Economic Journal: Economic Policy*, *10*(1), 240-267.

Kani, A. H., Abbasspour, M., & Abedi, Z. (2014). Estimation of demand function for natural gas in Iran: Evidences based on smooth transition regression models. *Economic Modelling*, *36*, 341-347.

Labandeira, X., Labeaga, J. M., & López-Otero, X. (2017). A meta-analysis on the price elasticity of energy demand. *Energy policy*, *102*, 549-568.

Lee, C. C., & Chiu, Y. B. (2011). Electricity demand elasticities and temperature: Evidence from panel smooth transition regression with instrumental variable approach. *Energy Economics*, *33*(5), 896-902.

Liddle, B. (2023). Is timing everything? Assessing the evidence on whether energy/electricity demand elasticities are time-varying. *Energy Economics*, *124*, 106872.

Liddle, B., Smyth, R., & Zhang, X. (2020). Time-varying income and price elasticities for energy demand: Evidence from a middle-income panel. *Energy economics*, *86*, 104681.

Moral-Carcedo, J., & Vicéns-Otero, J. (2005). Modelling the non-linear response of Spanish electricity demand to temperature variations. *Energy economics*, *27*(3), 477-494.

Mubiinzi, G., Senyonga, L., Kaawaase, T. K., Wasswa, F., Adaramola, M. S., & Nantongo, M. (2024). Income and price elasticities of household electricity demand: A comparative systematic review of aggregated and disaggregated data studies. *Energy Reports*, *12*, 4449-4465.

Muthuramu, P., & Maheswari, T. U. (2019). Tests for structural breaks in time series analysis: A review of recent development. *Shanlax International Journal of Economics*, *7*(4), 66-79.

Nawaz, S., Iqbal, N., & Anwar, S. (2014). Modelling electricity demand using the STAR (Smooth Transition Auto-Regressive) model in Pakistan. *Energy*, *78*, 535-542.

Pellini, E. (2021). Estimating income and price elasticities of residential electricity demand with Autometrics. *Energy Economics*, *101*, 105411.

Perron, P. (2010). Structural change, econometrics of. In *Macroeconometrics and Time Series Analysis* (pp. 288-302). London: Palgrave Macmillan UK.

Rapson, D. (2014). Durable goods and long-run electricity demand: Evidence from air conditioner purchase behavior. *Journal of Environmental Economics and Management*, *68*(1), 141-160.

Sahari, A. (2019). Electricity prices and consumers' long-term technology choices: Evidence from heating investments. *European Economic Review*, *114*, 19-53.

Yamaguchi, K. (2007). Estimating energy elasticity with structural changes in Japan. *Energy economics*, *29*(6), 1254-1259.

Appendix

A. Robustness to alternative demand specification: Linear Demand

The baseline analysis relies on a log–log specification that implies a constant price elasticity of demand. Estimated elasticities are quantitatively small, which raises the concern that proportional responses may provide an incomplete description of consumption behavior, particularly in the presence of large price changes. To address this concern, we estimate an alternative linear demand specification of the form $C = a + bP + e$. The linear model provides a flexible approximation of demand in levels and allows elasticities to vary with prices and consumption.

Unlike the log–log model, which implies identical proportional consumption responses to small and large price changes, the linear model assumes a constant marginal effect of prices and therefore allows the implied elasticity to vary over the observed price range. This distinction is particularly relevant in our setting, where prices exhibit substantial variation, making the constant elasticity assumption potentially restrictive.

	Dependent variable:	
	Volume	
	Electricity	Gas
Price	-0.574***	-27.162***
	(0.060)	(4.138)
Temperature	-18.903***	-45.369
	(1.794)	(48.914)
Daylight	-1.003*	-14.457
	(0.586)	(15.980)
Humidity Index	9.832***	-56.011
	(1.387)	(37.771)
Constant	1,262.899**	14,886.390
	(509.328)	(13,886.190)
DSO Fixed Effects	Yes	Yes
Monthly Fixed Effects	Yes	Yes
Observations	2,659	2,026
R2	0.882	0.671
Adjusted R2	0.881	0.666
Residual Std. Error	24.893 (df = 2623)	592.100 (df = 1995)
F Statistic	561.305*** (df = 35; 2623)	135.759*** (df = 30; 1995)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table A1: Linear Models for the Residential Electricity and Gas Markets

Table A1 highlights the results of the linear model for the residential electricity and gas markets. The models are estimated on the same sample and with the same set of controls as the baseline log–log specification. The results confirm the main qualitative findings of the baseline model: consumption remains negatively related to prices, the estimated price coefficients are statistically significant, and the signs of the control variables are consistent with expectations. While the linear model implies a different functional form for the price–consumption relationship, the overall qualitative patterns remain unchanged.

We compare the log-log and linear models in terms of goodness-of-fit. Because the two models are estimated on different dependent variables, conventional R^2 statistics are not directly comparable across specifications. Instead, we evaluate predictive performance in levels of electricity consumption for both models. For the log–log specification, fitted values are transformed back into levels using a smearing correction[12]. We then compare the root mean squared error (RMSE) and the mean absolute error (MAE) across models.

		Residential Electricity	Residential Gas
Log-log model	RMSE	81220815.16	301301301.23
	MAE	63909545.21	202515582.88
Linear model	RMSE	81220815.27	301301326.31
	MAE	63909545.22	202515598

Table A2: Goodness-of-fit comparison between the Linear and Iso-elastic Models

Table A2 reports the RMSE and MAE for both models across the two markets. Lower values of these error metrics indicate a superior model fit. For the electricity market, the log–log specification provides only a very slightly better fit to the data than the linear model, with RMSE and MAE almost identical. This finding suggests that proportional responses of consumption to price variation provide only a slightly more accurate summary of observed household electricity consumption over the sample period. For the gas market, the log–log model also outperforms the linear specification, although the improvement in fit is still moderate.

Overall, these results indicate that the log–log specification provides a better fit to the data than the linear model in both markets. Although the goodness-of-fit is only improved very slightly. Even though the implied elasticities remain small, the isoelastic approximation captures systematic variation in consumption more accurately than a linear demand function. Importantly, this comparison does not imply that demand is exactly isoelastic, but rather that the constant-elasticity approximation captures the dominant relationship between prices and consumption in the data better than the constant marginal approximation.

[12] When a regression is estimated with the dependent variable in logarithms, simply exponentiating the fitted log values produces biased predictions in levels because the nonlinear transformation does not preserve the mean. The smearing correction adjusts for this by multiplying the exponentiated fitted values by the average of the exponentiated residuals. This provides an unbiased estimate of the expected value of the dependent variable in its original units and avoids the systematic under-prediction that would occur without the adjustment.

B. Inference Theory

Given the panel structure of the data, the idiosyncratic error term may exhibit serial correlation within units over time. Under the maintained assumption of strict exogeneity of the regressors conditional on unit fixed effects, the fixed-effects estimator remains consistent in the presence of serial correlation. However, serial dependence violates the assumption of independence across time within units and renders conventional standard errors inconsistent, as the usual variance formula fails to account for the resulting within-cluster covariance structure. To obtain asymptotically valid inference, we therefore compute standard errors clustered at the unit level. This corresponds to a cluster-robust sandwich variance estimator that allows for arbitrary forms of heteroskedasticity and serial correlation within units, while maintaining independence across units. In the regime-specific specifications, the variance of the error term may additionally differ across regimes. Nonetheless, unit-level clustering remains appropriate, as the cluster-robust estimator places no restrictions on the within-unit variance–covariance matrix and thus accommodates regime-dependent heteroskedasticity as well as serial correlation. Consequently, the clustered variance estimator delivers consistent standard errors for all model specifications considered.

To assess the relevance of the regime-specific specifications, we test whether the price elasticity differs across regimes. Specifically, we test the null hypothesis that the elasticity is identical before and after the regime change against the alternative that it differs in at least one regime:

$H_0: \beta_L = \beta_H$ In the structural break model, this hypothesis can be tested using standard asymptotic inference, since the break date is known and imposed ex ante. Treating the break date as fixed avoids the nonstandard asymptotic distributions that arise when the break point is estimated endogenously. Consequently, the null hypothesis is evaluated using Wald test of linear restrictions on the estimated coefficients, computed with cluster-robust standard errors at the DSO level. This corresponds to a Chow-type test, where the null hypothesis of no break implies equality of coefficients across regimes. Rejection of the null hypothesis is interpreted as evidence of a structural change in the relationship between energy prices and demand at the imposed break date, conditional on the maintained assumption that the timing of the break is exogenous.

In the threshold model, testing for the presence of regime dependence is more involved because the threshold parameter θ is not identified under the null hypothesis of no threshold effect. Under H_0, the slope coefficients are identical across regimes, and the data provides no information about the location of the threshold; consequently, any candidate value of θ yields an equivalent fit. As a result, standard asymptotic inference is not applicable.

Inference is instead based on a likelihood ratio (LR) statistic that compares the fit of the threshold model to that of the null model without regime switching. Following Hansen (2000), the test statistic is defined as

$$F_1 = \sup_{\theta \in \Theta} \frac{SSR_0 - SSR(\theta)}{\hat{\sigma}^2},$$

where SSR_0 denotes the sum of squared residuals from the null model, $SSR(\theta)$ is the sum of squared residuals from the threshold model evaluated at a given candidate threshold θ, Θ is the admissible set of threshold values, and $\hat{\sigma}^2$ is a consistent estimator of the error variance. Because the threshold parameter is not identified under the null, the statistic involves a supremum over all admissible threshold values. This implies that F_1 corresponds to the maximum of a continuum of correlated chi-square–type statistics computed at different candidate thresholds. Consequently, its distribution is nonstandard, does not converge to a conventional chi-square distribution, and depends on sample-specific features such as the moments and correlation structure of the data.

To obtain valid inference in this setting, we follow Hansen (1999) and employ a residual-based bootstrap procedure to approximate the asymptotic distribution of the likelihood ratio statistic, denoted F_1. The bootstrap accounts for the nonstandard nature of the test statistic and delivers asymptotically valid p-values for testing the null hypothesis of no threshold effect.

Under the null hypothesis of no threshold effect, the model reduces to the linear fixed-effects specification given in equation (1). Let $\hat{u}_{it}$ denote the residuals from this null model. For each unit i, we collect the residuals over time into the vector $\hat{\mathrm{u}}_i = (\hat{u}_{i1}, \hat{u}_{i2}, \ldots, \hat{u}_{iT})$. The collection $\{\hat{\mathrm{u}}_1, \ldots, \hat{\mathrm{u}}_N\}$ is treated as an empirical distribution from which bootstrap samples are drawn.

Bootstrap resampling is conducted at the unit level by drawing, with replacement, N residual vectors $\hat{\mathrm{u}}_i$. Resampling entire residual vectors preserves the within-unit temporal dependence structure of the error process, including serial correlation and heteroskedasticity[13]. In contrast, resampling residuals period by period would destroy this dependence and lead to invalid inference. Throughout the bootstrap procedure, the regressors x_{it} and the threshold variable q_{it} are treated as fixed, and the coefficients estimated under the null hypothesis are held constant. Consequently, the bootstrap samples are explicitly anchored to the null specification, and all randomness arises solely from resampling the residuals.

Given a bootstrap draw $\hat{u}^*_{it}$, the bootstrap outcome variable is constructed under the null hypothesis as

$$y^*_{it} = \hat{y}^{(0)}_{it} + \hat{u}^*_{it},$$

where $\hat{y}^{(0)}_{it}$ denotes the fitted values from the null model. This procedure yields a bootstrap dataset $\{y^*_{it}, x_{it}, q_{it}\}$ that satisfies the null hypothesis of no threshold effect while incorporating resampled error variation. We repeat this procedure B times.

For each bootstrap sample, we re-estimate both the null model and the threshold model and compute the corresponding bootstrap likelihood ratio statistic, denoted F^*_1. The collection $\{F^*_1(1), \ldots, F^*_1(B)\}$ forms an empirical approximation to the sampling distribution of the test statistic under the null hypothesis. The bootstrap p-value is then computed as

$$\hat{p} = \frac{1}{B}\sum_{b=1}^{B} \mathbb{1}(F^*_1(b) \geq F_1),$$

where F_1 is the likelihood ratio statistic computed from the original sample. The null hypothesis of no threshold effect is rejected if the bootstrap p-value is smaller than the chosen significance level.

[13] Resampling residual vectors at the unit level is equivalent to a block bootstrap with block length equal to the time dimension and ensures validity in the presence of serial correlation and heteroskedasticity within units.

For each specification, we report confidence intervals for the estimated slope coefficients. In the constant elasticity and structural break models, confidence intervals are constructed using standard asymptotic normal approximations based on unit-level cluster-robust variance estimators. Constructing confidence intervals in the threshold model is less straightforward because the slope coefficients depend on the estimated threshold parameter. However, Hansen (1999) shows that the uncertainty associated with estimating the threshold is asymptotically negligible for inference on the slope coefficients. Specifically, the threshold estimator converges at a faster rate than the slope coefficients, so its estimation error does not affect the first-order asymptotic distribution of the regression parameters. As a result, the slope estimators are asymptotically normal and can be treated, for inference purposes, as if the true threshold were known. Consequently, confidence intervals for the slope coefficients in the threshold model are constructed using standard asymptotic methods based on cluster-robust variance estimates.

C. Non-residential sector results

This section presents the regression results for the non-residential electricity and gas sectors. By *non-residential*, we refer to all firms connected to the distribution grid that are subject to professional supply contracts, that is, tariffs specifically designed for firms. Although these prices are contractually distinct, their levels remain close to residential prices, with professional contracts not subject to VAT.

Relative to the previous regressions, the non-residential electricity models include an additional control variable capturing self-produced electricity. This control accounts for firms' ability to partially substitute grid electricity with internal generation. Apart from this extension, the empirical framework remains comparable to that used in earlier sections.

A key limitation of these specifications is the potential endogeneity of energy consumption in the non-residential sector. Firms' electricity and gas demand are closely linked to business cycle fluctuations, which simultaneously affect output, energy use, and potentially energy prices. As a result, the estimated elasticities reflect a combination of consumption-price responses and endogenous price movements and should be interpreted with caution.

Several results emerge from Tables C1 and C2. First, price elasticities are consistently low in magnitude across all specifications, suggesting limited short-run price responsiveness of non-residential energy demand. For instance, in the constant-elasticity models, the estimated price elasticity of electricity demand is −0.052 ($p < 0.01$), while the corresponding estimate for gas is −0.042 ($p < 0.01$). These values indicate that a 10% increase in energy prices is associated with a reduction in consumption of approximately 0.4–0.5%.

Second, the regime-dependent specifications reveal modest differences in price responsiveness across price regimes. In the structural break model for electricity, the elasticity in the pre-break regime is estimated at −0.030 ($p < 0.01$), compared to −0.038 ($p < 0.01$) in the post-break regime. The threshold model yields slightly larger elasticities, with estimates of −0.053 ($p < 0.01$) and −0.046 ($p < 0.01$) for the low- and high-price regimes, respectively. For gas, the structural break model shows no difference between regimes, with an elasticity of −0.042 in both cases, although the low-price estimate is not statistically significant. In contrast, the threshold model suggests stronger price responsiveness in the low-price regime (−0.083, $p < 0.01$) relative to the high-price regime (−0.046, $p < 0.01$).

As in the previous sections, the differences across model specifications reflect the fact that the structural break and threshold models capture distinct sources of non-linearity and assign observations to regimes using different criteria. The structural break model classifies observations based on whether they occur before or after the onset of the energy crisis and therefore identifies a crisis-related effect. By contrast, the threshold model categorizes observations according to whether prices lie above or below a given threshold level, thereby capturing a price-level effect. As a result, the estimated elasticities from these models reflect different mechanisms.

	Dependent variable:		
		Consumption	
	Const. Elast. Model	Struct. Break Model	Threshold Model
Price	-0.052***		
	(0.004)		
Price Regime			
Low Price		-0.030***	-0.053***
		(0.008)	(0.006)
High Price		-0.038***	-0.046***
		(0.006)	(0.005)
Temperature	-0.043***	-0.043***	-0.043***
	(0.009)	(0.009)	(0.010)
Daylight	-3.242**	-3.475***	-3.107**
	(1.301)	(1.298)	(1.436)
Humidity Index	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)
Auto Produced	-0.038***	-0.037***	-0.040***
	(0.003)	(0.003)	(0.004)
Constant	30.865***	32.387***	29.825***
	(8.802)	(8.781)	(9.721)
DSO Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Observations	2,653	2,653	2,286
R2	0.947	0.947	0.948
Adjusted R2	0.946	0.946	0.947
Residual Std. Error	0.076 (df = 2616)	0.076 (df = 2615)	0.079 (df = 2251)
F Statistic	1,293.441*** (df = 36; 2616)	1,261.380*** (df = 37; 2615)	1,211.760*** (df = 34; 2251)
Note:			*p<0.1; **p<0.05; ***p<0.01
			Standard errors are clustered at the unit (DSO) level.

Table C1: Non-residential Electricity Models

	Dependent variable:		
	Consumption		
	Const. Elast. Model	Struct. Break Model	Threshold Model
Price	-0.042***		
	(0.008)		
Price Regime			
Low Price		-0.042	-0.083***
		(0.029)	(0.017)
High Price		-0.042***	-0.046***
		(0.013)	(0.008)
Temperature	-0.344***	-0.344***	-0.361***
	(0.033)	(0.033)	(0.032)
Daylight	-5.129	-5.129	-6.413*
	(3.391)	(3.374)	(3.414)
Humidity Index	0.036***	0.036***	0.039***
	(0.006)	(0.006)	(0.006)
Constant	44.126*	44.120*	52.864**
	(22.944)	(22.831)	(23.102)
DSO Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Observations	2,032	2,032	2,032
R2	0.936	0.936	0.936
Adjusted R2	0.935	0.935	0.935
Residual Std. Error	0.185 (df = 2001)	0.185 (df = 2000)	0.185 (df = 2000)
F Statistic	975.864*** (df = 30; 2001)	943.913*** (df = 31; 2000)	946.139*** (df = 31; 2000)
Note:			*p<0.1; **p<0.05; ***p<0.01
			Standard errors are clustered at the unit (DSO) level.

Table C2: Non-residential Gas Models