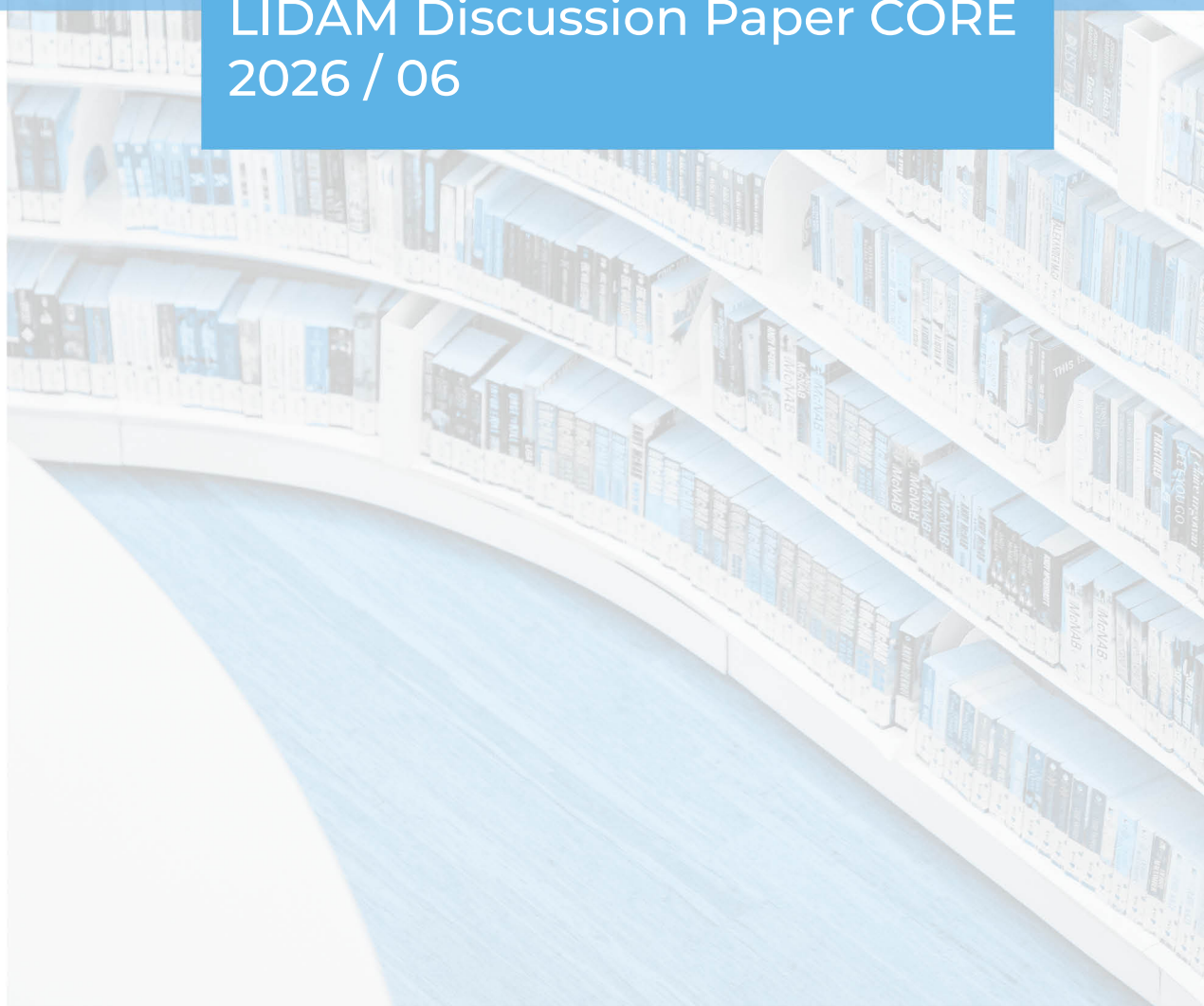
REVISITING ENERGY DEMAND ELASTICITY: THE POWER OF REGIME SWITCH

Jean Hindriks, Lucie Paré, Valerio Serse

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Revisiting Energy Demand Elasticity: The power of regime switch[1]

Jean Hindriks, Lucie Paré and Valerio Serse[2]

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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. Because prices are nearly flat outside the crisis, the constant elasticity estimate is dominated by crisis-period variation and may poorly describe responses under normal market conditions. The two regime-based models reveal different patterns. In the structural break model, responsiveness is larger after the onset of the crisis for both electricity and gas, and for gas it is undetectable before the crisis; this cannot be separated from other crisis-related factors. In the threshold model, elasticities are significant in both regimes but smaller in magnitude at high prices for both markets, consistent with weaker responsiveness during high-price periods. These results suggest that the two specifications capture distinct dimensions of price responsiveness (price level versus price variance), and that the choice of regime-identification strategy shapes which type of response is detected.

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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[2] Jean Hindriks and Lucie Paré are researchers at LIDAM-CORE, UCLouvain. Valerio Serse is senior economist at Compass Lexecon-Brussels and Research affiliate at LIDAM-CORE, UCLouvain.

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 150% for residential electricity and 180% 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, a parameter that is central to policy design. Price elasticities determine how far consumption, and hence emissions, respond to instruments such as carbon taxes or energy levies, and how much support is needed when prices spike.

As shown by meta-analysis, residential gas and electricity demand is widely found to be price inelastic, particularly in the short run (Kudela et al., 2026, Labandeira et al., 2017). However, estimates vary considerably across studies. Results depend on the type of data, the model specification, and the estimation technique, with aggregate data often yielding smaller elasticities than micro-level household data (Labandeira et al., 2017, Mubiinzi et al., 2024). Country, time period, and tariff structure also account for a significant share of this heterogeneity (Espey & Espey, 2004). Most of this empirical literature relies on relatively small price variations, and evidence on household responses to large price shocks remains scarce. This matters for policy, because elasticities are often applied to price changes that differ from those in the estimation sample, and a single elasticity may not describe responsiveness across very different price environments.

Prior to the energy crisis, 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 Belgian 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). It 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 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.

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 and gas demand.

Our analysis also 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.

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[3]. 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.

Our results show that the commonly used constant-elasticity specification can give a misleading picture of demand responses when price variation is large and uneven. In our data, prices are almost flat in normal times, and most of the variation occurs during the energy crisis. A constant-elasticity model imposes a single price slope on the whole sample, so the pooled estimate is dominated by the crisis period and is a biased summary of how consumers respond under normal market conditions. These findings point to a general limitation of log-log demand models in environments with large and abrupt price fluctuations. This has direct policy implications: an elasticity driven by crisis-period variation may misstate how households respond to instruments such as carbon taxes, which operate around normal price levels, and over- or underestimating responsiveness can change policy conclusions.

We further show that demand responses to energy prices are regime-dependent in both electricity and gas markets, but that the pattern depends on how regimes are defined. When regimes are defined by the price level (threshold model), elasticities are significant in both regimes and smaller in magnitude at high prices, for electricity (from -0.198 to -0.178) and for gas (from -0.201 to -0.150). This is consistent with weaker responsiveness as prices rise, as expected for a necessity good. When regimes are defined by time (structural break model), the pattern reverses: responsiveness is larger after the onset of the crisis, and for gas it is statistically undetectable before the crisis. The two specifications therefore capture different dimensions of price response; one tied to the price level and the other to the variance and salience of the crisis-period price shock. Overall, the results show that the choice of regime-identification strategy shapes which type of response is detected.

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 empirical results. Finally, Section 5 concludes.

[3] In the threshold model, the high- and low-price regimes are identified endogenously by the model. By contrast, in the structural break model, the high-price regime is defined by the onset of the energy crisis, when prices rose substantially relative to the pre-crisis period. We therefore refer to this period as the high-price regime, although the regime classification is not based directly on the price level.

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 which has exhibited substantial volatility 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 underlining 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 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 regulated certificate-related charges: the green certificate fee and the cogeneration (WKK) fee. Their amounts vary across regions and across contracts, as suppliers determine how these legally imposed costs are passed through to consumers. Moreover, each contract specifies different prices depending on the type of electricity meter installed. Consistent with CREG's own tariff comparison methodology[4], 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[5], 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 each 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.

[4] Each year, CREG performs a study comparing the European electricity and natural gas prices for residential, small professionals, and large industrial consumers.

[5] Example of indexation formula: Price = Mark-up + (Coeff x Index variable). The Mark-up, Coeff, and choice of 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 market.

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 series. To do so, we distinguish between two price concepts: a marginal price series and an average 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*[6], 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 fixed price by this simple rolling average.

The average 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 employed in this aggregation reflect the proportion of households holding fixed-price contracts. Since this proportion is not directly observable at a monthly frequency, we draw on estimates published by the Flemish energy regulator (VREG), which reports these shares quarterly for the Flemish region. These figures are, however, broadly consistent with those observed for the population. It should be noted that, over the course of the energy crisis, fixed-price contracts progressively disappeared as their associated risk premium rose sharply, resulting in a substantial decline in coverage. At the height of the crisis, fewer than 25% of households remained under fixed-price contracts (CREG, 2023).

Figures 1 and 2 display these two-price series for households in the electricity and gas markets, respectively, each computed as the average across DSOs. Prices rose sharply after 2022, a trend initially driven by the post-COVID recovery, as surging demand met constrained supply chains. This upward pressure was further exacerbated by the Russian invasion of Ukraine in February 2022, which pushed prices well above historical levels. As shown in the figures, the peak in the average price series is considerably lower than that of the marginal price series and occurs with a slight delay. This illustrates the smoothing effect of fixed-rate contracts on the energy price shock.

Because households pay VAT on energy consumption, the price series in figures 1 and 2 are VAT-inclusive. 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

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

reduction was introduced in direct response to heightened energy prices, whereas the former VAT change was (plausibly) exogenous[7].

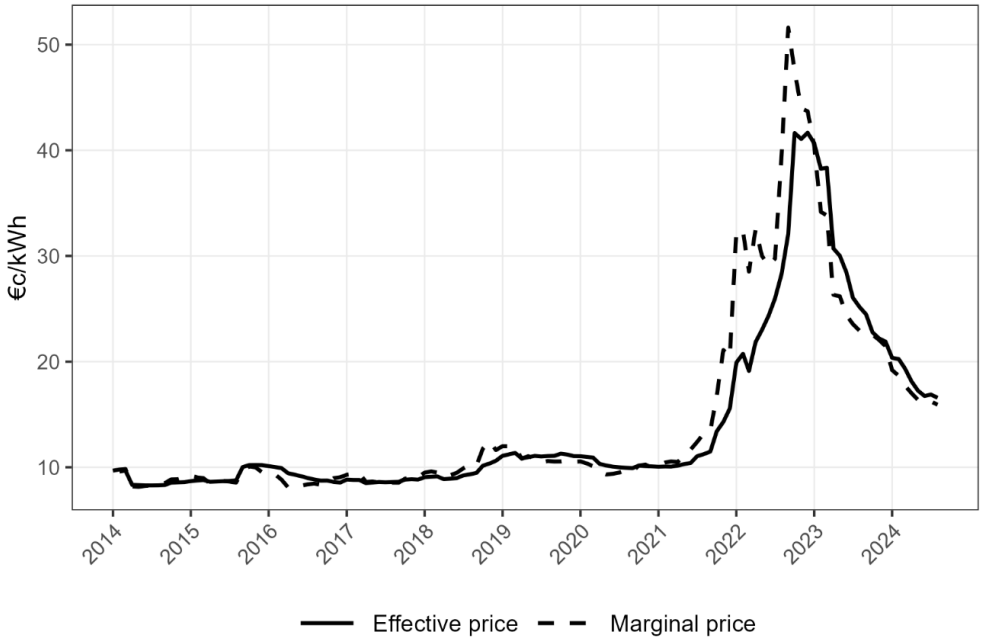


FIGURE 1: Residential Electricity prices

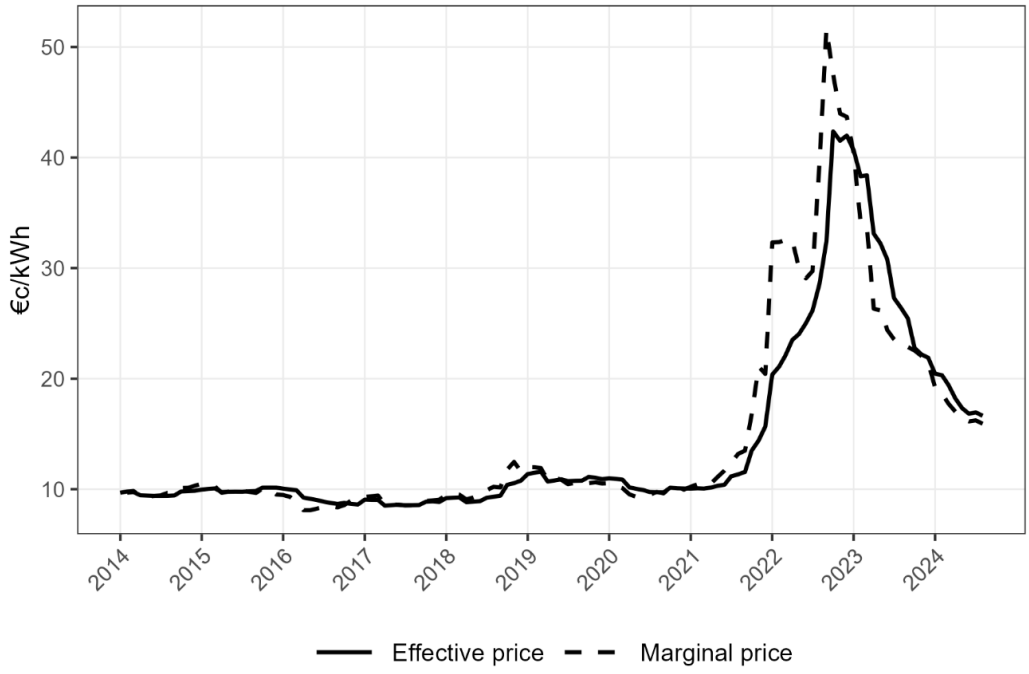


FIGURE 2: Residential Gas prices

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

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), incorporating these additional charges is nonetheless important for analyzing consumer behavior. Together, these components represent a substantial share of the 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. Retaining the full sample period is preferable to retain enough observations before the energy crisis peaks. 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.

Incorporating those price components into the price series would also have allowed for greater price variability across DSOs. Here, price disparities are explained by regional rather than DSO-level differences. In principle, tariff schedules are defined at the regional level, so energy providers could set different prices across regions; in practice, however, such differences are limited, particularly among large providers such as Luminus and Engie. For the electricity market, regional price differences mainly stem from green certificate schemes, whose rates vary across regions, and cogeneration fees, which are specific to Flanders. Hence, within a given region, prices are identical across DSOs, since our series are built from regionally published tariff sheets

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 16 DSOs for the gas market and 22 DSOs for the electricity market, this yields a total of 32 and 42 consumption time series, respectively. 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.

Figures 3 and 4 illustrate the evolution of monthly average 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 up to the summer of 2021. However, consumption in the summer of 2022 is much higher relative to the previous years. This is particularly intriguing given that electricity prices reach an all-time high during the same period. One would have expected that electricity consumption decreased during that period. 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.

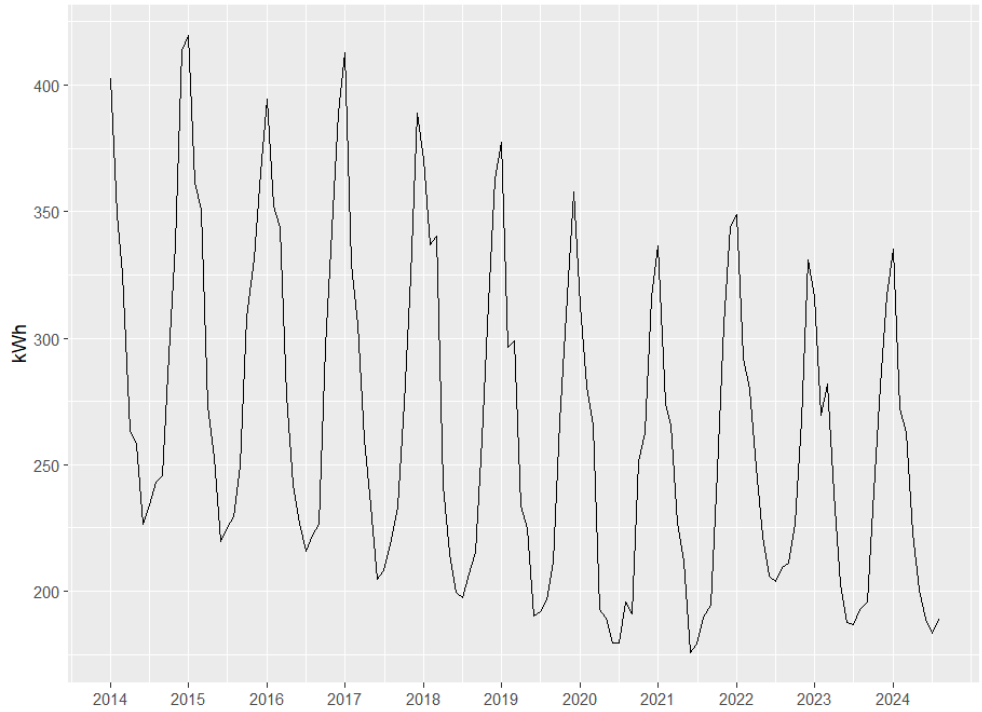


FIGURE 3: Belgium's Average Residential Electricity Consumption

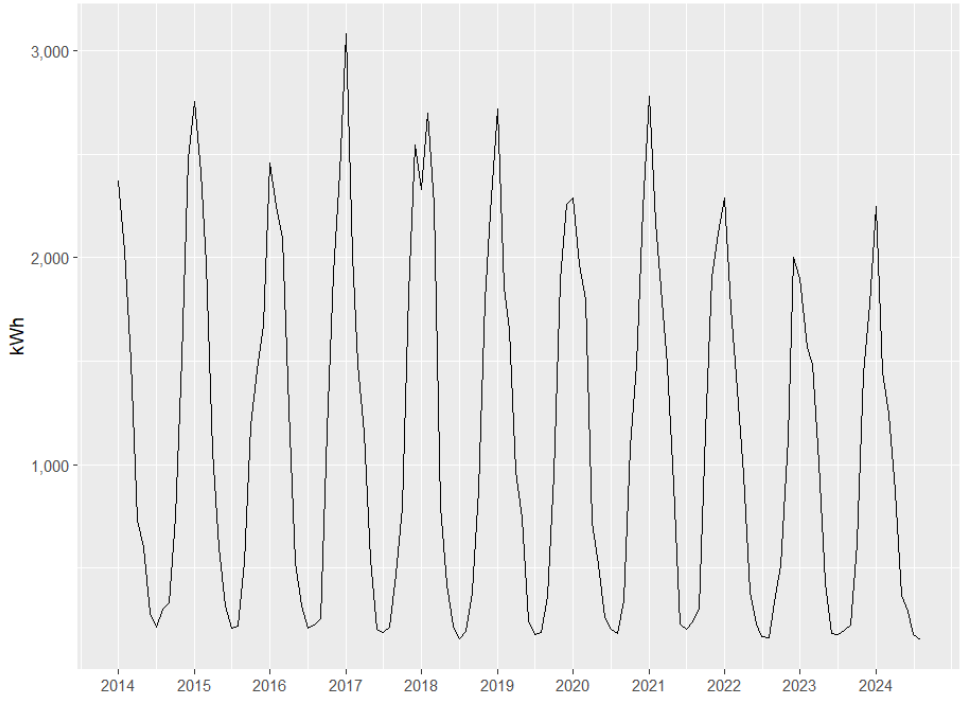


FIGURE 4: Belgium's Average Residential Gas Consumption

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.

	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)	282.59	76.74	234.87	90.71
Average Residential Gas Consumption (kWh)	1215.88	893.54	979.89	1276.32
Residential Electricity Prices (€c/kWh)	9.57	1.00	23.98	8.76
Residential Gas Price (€c/kWh)	3.18	0.43	8.90	4.08
Daylight	737.30	174.14	744.86	175.88
Temperature	11.08	5.41	12.04	5.39
Humidity Index	11.47	7.14	12.85	7.14

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

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 comparison across periods reveals substantial shifts in both averages and variability for the energy market variables, while meteorological variables remain comparatively stable. Both electricity and gas prices rose sharply on average and became considerably more volatile: electricity price volatility (measured by the standard deviation) increased from 1.00 to 8.76, while gas price volatility rose from 0.43 to 4.08. Over the same period, average energy consumption declined. Electricity consumption fell from 282.59 kWh to 234.87 kWh and gas consumption fell from 1215.88 kWh to 979.89 kWh. While this reduction in consumption may partly reflect the sharp rise in energy prices, it may also be attributed to more favorable meteorological conditions during the period. Since consumption is shaped by multiple factors beyond price, these shifts should not be interpreted as a causal price response.

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 change as a function of the price or consumption level. 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 allow price elasticities to differ between periods of low and high energy prices. Each specification is estimated separately for the residential sector in each market.

With the constant elasticity specification, we are not assuming that the true demand function is isoelastic, that is, that the proportional consumption response to price change is independent of the price level. The constant elasticity model 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 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[8]. Only in the special case where the demand function is iso-elastic does the log-log model coincide exactly with the underlying demand function.

We estimate the constant elasticity model using a log-log specification, which is widely used in electricity and natural gas demand estimation because of its 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, and, for 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

[8] 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 constant elasticity. Both models highlight different aspects of the price-consumption relationship.

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 on our dataset. These persistent differences affect both the level of electricity consumption and the 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 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., $E[\varepsilon_{it} \mid P_{i1}, \ldots, P_{it}, \mu_i] = 0$. 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.

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 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.

A motivation for introducing these models is the pronounced heterogeneity in volatility across price regimes. Both residential electricity and gas prices show substantially higher variance during the energy crisis compared to the earlier period. Consumption volatility rises as well for both goods over the same horizon. Failing to account for this regime-dependent heteroskedasticity may lead to inefficient estimation (and misleading inference). One possible explanation for this pattern is a change in the underlying price elasticity of demand across regimes; while volatility alone cannot confirm such a shift, it provides sufficient grounds to formally test for a structural break in the price-demand relationship.

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:

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

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.

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 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 a plausibly unexpected and externally imposed shock. Although a number of policy measures, such as the VAT reduction, the extension of social tariffs, and the 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 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).[9] 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 exceeds a parameter θ. The model can be expressed as:

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

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 a constant which captures 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

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

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, 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 $\widehat{\beta} = \beta(\widehat{\theta})$.

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

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 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 enough 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 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.

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 energy consumption and the control variables do not depend on the specification adopted.

Residential Electricity with VAT

	Dependent variable:		
	Consumption		
	Const. Elast. Model	Struct. Break Model	Threshold Model
Prices	-0.190***		
	(0.008)		
Price Regime			
Low Prices		-0.105***	-0.198***
		(0.019)	(0.012)
High Prices		-0.133***	-0.178***
		(0.014)	(0.008)
Temperature	-0.162***	-0.165***	-0.161***
	(0.015)	(0.015)	(0.016)
Daylight	-4.836*	-5.855**	-4.725*
	(2.511)	(2.533)	(2.603)
Humidity Index	0.018***	0.019***	0.018***
	(0.002)	(0.002)	(0.003)
Constant	38.988**	45.711***	38.252**
	(16.999)	(17.142)	(17.624)
DSO Fixed Effects	Yes	Yes	Yes
Monthly Fixed Effects	Yes	Yes	Yes
Observations	2,658	2,658	2,540
R2	0.764	0.767	0.758
Adjusted R2	0.761	0.764	0.754
Residual Std. Error	0.145 (df = 2622)	0.145 (df = 2621)	0.148 (df = 2504)
F Statistic	243.191*** (df = 35; 2622)	239.467*** (df = 36; 2621)	223.748*** (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 fixed 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 0.76 for the electricity market and up to 0.97 for the gas market, across all specifications. Although these values may appear unusually high, particularly for gas, they are explained by the rich set of regressors and fixed effects included in the models: 35 and 30 regressors in the constant elasticity model for electricity and gas respectively. Hindriks and Serse (2022) also find high R^2 values, using similar empirical approach using comparable data. Though, 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 2,658 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 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 with VAT

	Dependent variable:		
	Consumption		
	Const. Elast. Model	Struct. Break Model	Threshold Model
Prices	-0.150***		
	(0.006)		
Price Regime			
Low Prices		-0.029	-0.201***
		(0.026)	(0.013)
High Prices		-0.095***	-0.150***
		(0.013)	(0.007)
Temperature	-0.617***	-0.615***	-0.638***
	(0.039)	(0.039)	(0.037)
Daylight	-9.716***	-9.954***	-12.392***
	(3.228)	(3.109)	(3.258)
Humidity Index	0.068***	0.068***	0.072***
	(0.005)	(0.005)	(0.005)
Constant	72.827***	74.309***	91.002***
	(21.821)	(21.021)	(22.028)
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	0.971
Residual Std. Error	0.160 (df = 1995)	0.159 (df = 1994)	0.162 (df = 1994)
F Statistic	2,323.673*** (df = 30; 1995)	2,290.265*** (df = 31; 1994)	2,210.155*** (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 -0.19 for the electricity market and -0.15 for the gas market. These estimates imply that on average a 1% increase in electricity prices reduces grid electricity consumption by approximately 0.19% and a 1% increase in gas prices reduces gas consumption by 0.15%.

These elasticities fall within the range of short run price elasticities reported in the literature. A large meta-analysis covering 4,720 estimates from 462 studies estimates an average elasticity of electricity demand of approximately -0.16 in the short term and -0.38 in the long term (Kudela et al. 2026). For natural gas, no comparable meta-analysis exists for Europe, though a meta-study covering all energy sources reports an average short-run gas elasticity of -0.18 (Labandeira et al., 2017).

These benchmarks should be interpreted with caution, as estimated elasticities are strongly influenced by the type of data, the model specification, and the estimation technique. For instance, Kudela et al. (2026) note that elasticities are smaller in absolute value in studies using more credible estimation methods. Context, including the period and country studied, also plays a critical role in explaining heterogeneity. Hindriks and Serse (2022), using similar Belgian data, report residential price elasticities ranging from -0.09 to -0.17. However, their sample covers only 2013-2016, a pre-crisis period in which price variation was much lower than during the energy crisis. Our two alternative regime specifications allow us to estimate regime-specific elasticities accounting for the crisis period, when prices were considerably higher.

A first observation from the results tables is that the structural break model (Model 2) and the threshold model (Model 3) produce drastically 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.

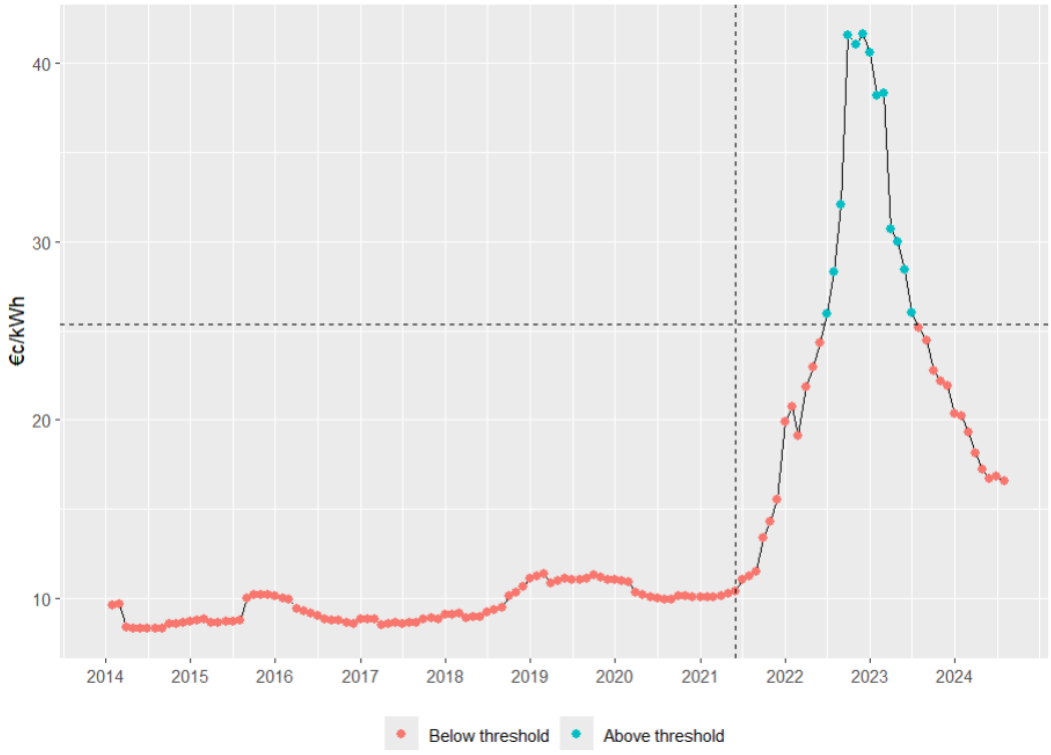


FIGURE 5: Electricity Price Regime Classification: Structural Break versus Threshold Models

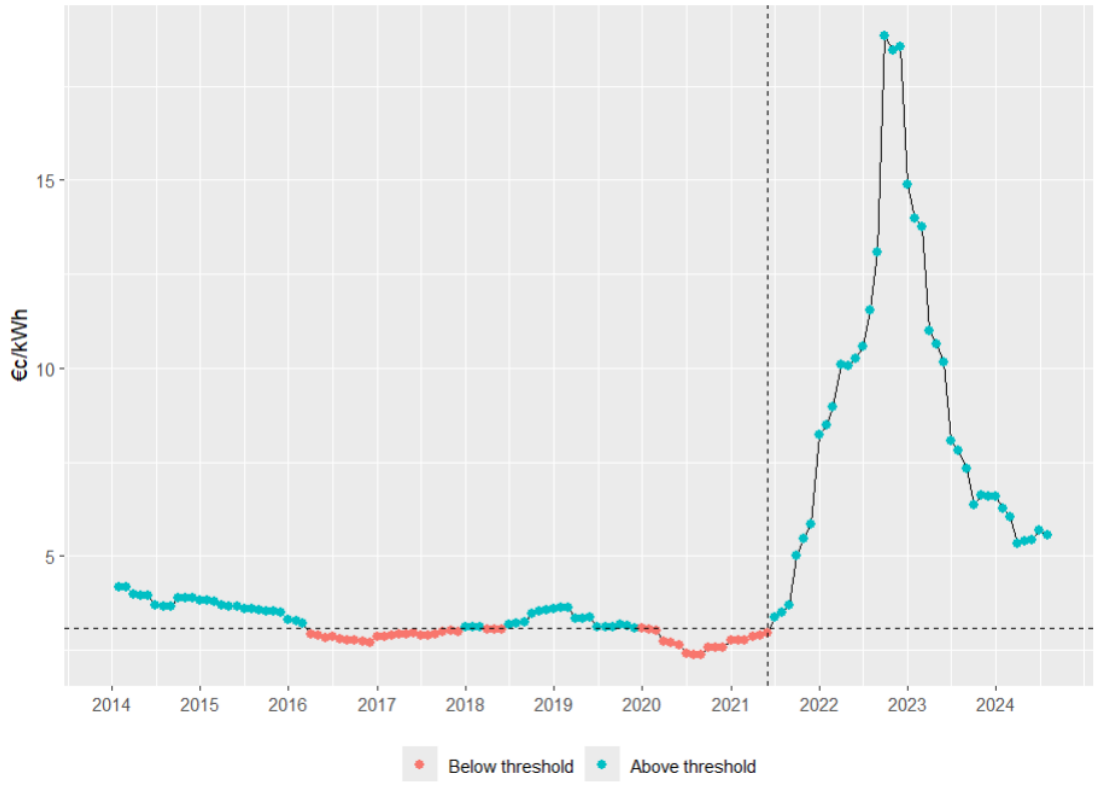


FIGURE 6: Gas Price Regime Classification: Structural Break versus Threshold Models

By partitioning the sample differently, the two models capture different sources of variation. The threshold model captures nonlinear responses associated with the price level, whereas the structural break model captures changes in overall responsiveness following the onset of the energy crisis. Because the crisis period coincides with the price surge, the structural break elasticities may also reflect factors other than the pure price effect such as the increased salience of energy prices (e.g., media coverage and public attention), government support measures, degree of price exposition (i.e., the proportion in fixed and variable contracts). These factors are not separately identified in the current specification and are likely confounded with the price variable.

The two regime-based specifications yield qualitatively different results for both markets, revealing a contrast in how price responsiveness evolves across regimes depending on model choice. In the structural break model, price elasticity increases in magnitude from the low-price (pre-crisis) to the high-price (crisis) regime for both electricity (from −0.105 to −0.133) and gas (from −0.029, n.s., to −0.095). The threshold model, by contrast, shows the opposite pattern: elasticity magnitude declines from the low- to the high-price regime. For electricity, the threshold estimates fall from −0.198 in the low-price regime to −0.178 in the high-price regime, while for gas they fall from −0.201 in the low-price regime to −0.150 in the high-price regime. All price elasticity estimates from the threshold models are statistically significant.

This divergence suggests that the two identification strategies capture different aspects of demand response. The structural break model, which imposes a single break associated with the crisis period, indicates that consumers became more responsive after the crisis began. It is particularly evident for gas, where responsiveness was undetectable before the crisis and emerges only afterwards. Because the crisis coincided with the price surge, this increase may reflect not only higher prices but also crisis-specific factors. The threshold model, which instead classifies price regimes based on the price level itself rather than a fixed time break, suggests that consumers are more price-elastic when prices are

relatively low, with this sensitivity attenuating as prices rise into higher brackets. This finding aligns with the notion that energy is a necessity good, such that as prices continue to rise, further reductions in consumption become progressively harder to achieve.

The results of the structural break model are qualitatively similar to those of Gabreyohannes (2010) and Kani et al. (2014). Gabreyohannes (2010) shows that price changes have no statistically significant effect on consumption when they remain below a certain threshold, whereas sufficiently large increases trigger a significant demand response. Kani et al. (2014) similarly finds that significant reductions in gas consumption occur only once prices exceed a certain level, while in the low-price regime the estimated elasticity is even positive. In our case, however, the emergence of a response after the break may reflect a heightened behavioral response to the scale and salience of the crisis-period price increase, rather than a stable, price-level-dependent threshold. Disentangling these channels is left for future work. The threshold model findings, by contrast, align more closely with Nawaz et al. (2014), who show that the impact of electricity prices diminishes as the price level rises. However, whereas Nawaz et al. (2014) find that the effect becomes statistically insignificant beyond a certain threshold, our estimates remain significant in both regimes.

Taken together, these results suggest that the two specifications are not competing estimates of a single underlying relationship but capture distinct dimensions of price responsiveness. The structural break model may reflect a behavioral response to the scale and salience of a large, discrete price shock, in line with the findings of Gabreyohannes (2010) and Kani et al. (2014). The threshold model, by contrast, points to a more general attenuation of responsiveness as price levels rise above threshold, in line with Nawaz et al. (2014) and consistent with energy being a necessity good. This is suggestive of at least two mechanisms shaping price responsiveness: one related to the size and salience of price changes, the other to the absolute price level. Because the crisis coincided with the price surge, however, the break model may also capture other crisis-related factors which are not disentangled here. More broadly, the choice of regime-identification strategy is not a purely technical one: it influences which type of response a model is likely to detect, and results should be interpreted accordingly.

Another interesting result is a statistical inversion, also known as *Simpson's paradox of aggregation*. For both the electricity and gas markets, the elasticity estimate for the full sample lies outside the range of the elasticity estimates obtained for the two sub-periods in the structural-break model. For electricity, the estimated price elasticity is −0.19 over the full period, compared with −0.105 before the break and −0.133 after the break. Similarly, for gas, the full-sample elasticity is −0.15, compared with −0.029 before the break and −0.095 after the break. Simpson's paradox occurs when the relationship observed within separate groups differs from, or even reverses, the relationship observed after the groups are combined. In this case, the difference arises partly because the two sub-periods account for very different numbers of observations, so the full-sample estimate is not simply an average of the two sub-period estimates. But there is another more subtle effect at work, as explained below, which is the omitted variable bias.

Now we turn to the assessment of whether regime-dependent specifications provide a statistically better fit. In the structural break models, we test whether the price elasticity of consumption changes after the break date (July 2021). The model allows a separate price coefficient in each regime, β_low before the break and β_high after it. We test the null hypothesis of parameter stability, H_o: β_high =

β_low, against the alternative that the elasticity differs across regimes, using a Wald test. 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 $F(1, 2621) = 21.86$ ($p < 0.001$), 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 $F(1, 1994) = 20.37$ with a p-value below 0.001. This provides strong evidence of a structural change in the price-consumption relationship after June 2021.

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 $\hat{\theta} = 25.77$ €c/kWh. Based on the bootstrap likelihood ratio test, which yields an LR statistic of 158.86 and a bootstrap p-value of 0.37, 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 $\hat{\theta} = 10.13$ €c/kWh with an LR statistic of 76.72 and a corresponding p-value of 0.39. Taking 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. Hansen (1996) 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. 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.

The omitted-variable bias

Importantly, the inability to statistically favor the threshold specification over the constant-elasticity model does not imply that the latter is an adequate description of demand. A constant-elasticity model imposes a single price slope on the whole sample. If the true elasticity differs across price regimes, the model omits a regime-specific slope. This omitted term is correlated with log price, and it is the regime-specific slope that picks up this correlation. How the correlation arises differs between our two specifications. In the threshold model, the regime is defined by the price itself: an observation belongs to the high-price regime when its price exceeds the threshold. The regime indicator, and hence the omitted slope term, is therefore mechanically related to log price. In the structural-break model, the regime is defined by calendar date rather than by price. The correlation is then not mechanical but empirical: it arises because prices were high during the crisis period, so the crisis dates largely coincide with high-price observations. Its strength depends on how closely the two coincide. In both cases, the high-price regime is where most of the price variation occurs, and the pooled estimate therefore absorbs part of the regime difference. This is a standard omitted-variable bias.

The nature of the bias follows from how price variation is distributed. Under normal market conditions prices are almost flat, whereas the energy crisis period features sharp increases and decreases that deviate substantially from the typical range. To see the bias explicitly, let x denote log price, y log

[10] The theory behind the inference results are presented in Appendix B.

consumption, and D an indicator equal to one in the high-price regime. Suppose the true model lets only the elasticity differ across regimes:

$$y = \alpha + \beta_1 x + (\beta_2 - \beta_1) \cdot (D \cdot x) + \varepsilon,$$

where β_1 and β_2 are the low-price and high-price elasticities. The constant-elasticity model estimates a single slope and therefore omits the term $z = D \cdot x$. The omitted-variable formula states that the pooled slope equals the true slope on x plus the true coefficient on the omitted term times the slope from regressing the omitted term z on x:

$$\beta_pooled = \beta_1 + (\beta_2 - \beta_1) \cdot \mathrm{Cov}(x, z)/\mathrm{Var}(x).$$

Calling the last term γ, this can be rewritten as

$$\beta_pooled = (1 - \gamma)\beta_1 + \gamma\beta_2.$$

The pooled elasticity therefore weighs the two regime elasticities by $(1 - \gamma)$ and γ, and its bias relative to the low-price (normal conditions) elasticity is $\gamma(\beta_2 - \beta_1)$. The bias disappears if the two elasticities are equal, or if the omitted term is unrelated to log price $(\gamma = 0)$. The weight γ tend to be large when the high-price regime carries most of the variation in log price. This is the case in an energy crisis: prices are nearly flat in the normal regime, so almost all identifying variation comes from the high-price regime. Consumer responses under normal conditions are then weakly identified, and the pooled elasticity mostly reflects the crisis period.

The weight γ is a regression coefficient rather than a convex weight, so it is not restricted to [0, 1], and the pooled elasticity is not necessarily bounded by β_1 and β_2. To see why, we split Cov(x, z) into within-regime and between-regime parts using the law of total covariance:

$$\gamma = \mathrm{Cov}(x, z)/\mathrm{Var}(x) = \tilde{n}_2 V_2/V + \tilde{n}_1 \tilde{n}_2 (\bar{x}_2 - \bar{x}_1) \cdot \bar{x}_2/V,$$

where $\tilde{n}_j$ is the share of observations in regime j, V_j the variance of log price within regime j, V the total variance of log price, and $\bar{x}_j$ the mean log price in regime j. The omitted term $z = D \cdot x$ is zero in the low-price regime and equals x in the high-price regime. Its mean is therefore zero in regime 1 and $\bar{x}_2$ in regime 2.

The first term is the within-regime part. Only regime 2 contributes, and there z = x, so the within-regime covariance is simply V_2. This term is the share of total price variation coming from the high-price regime, and it lies between 0 and 1 − η, where η is the share of price variance lying between regimes. The second term is the between-regime part. It arises because the regimes differ in mean log price $(\bar{x}_2 - \bar{x}_1)$ and in the mean of the omitted term $(\bar{x}_2 - 0 = \bar{x}_2)$. It can be written as $\eta \cdot \bar{x}_2/(\bar{x}_2 - \bar{x}_1)$. The same weights follow from the decomposition of the pooled slope[11].

The weight γ can leave [0, 1] only through the between-regime part, because the within-regime part cannot exceed 1 − η. The between-regime part depends on the level of mean log prices, not only on their variation. It pushes γ above one when the low-price regime contributes little price variation, as when prices are almost comparatively flat in normal times, and when the average log price is large

[11] Splitting Cov(x, y) into within-regime and between-regime parts gives a between term proportional to the difference in mean log consumption, $\bar{y}_2 - \bar{y}_1$. When the regimes share an intercept, $\bar{y}_2 - \bar{y}_1 = \beta_2\bar{x}_2 - \beta_1\bar{x}_1$. Substituting this and collecting terms, the coefficient on β_2 is exactly γ and the coefficient on β_1 is 1 − γ. The difference in average consumption in the between term therefore becomes the factor $\bar{x}_2$ in the expression for γ.

relative to the gap between the regime means. The pooled slope then extrapolates beyond β_2, so the pooled elasticity is more extreme than both regime elasticities. γ turns negative in the opposite case, when the mean log price of the low-price regime is sufficiently negative.

Our estimates show both patterns, with γ inside and outside [0, 1]. In the threshold models, the pooled elasticity lies within the range of the regime elasticities, consistent with identification being driven by the crisis period. In the structural-break models, the pooled elasticity is more negative than both regime elasticities, i.e., γ is outside [0, 1], so the constant-elasticity model overstates responsiveness relative to either regime. In both cases the pooled estimate is a biased summary of behavior under normal market conditions, although the magnitude varies across models and is small for electricity under the threshold specification.

The regime model is the simplest way to let the elasticity vary with price, and the same logic applies more generally. Price elasticity of demand is the percentage change in consumption resulting from a one percent change in price. The point elasticity at price p is a local property of the demand function, describing responsiveness in the immediate neighborhood of a given price-quantity combination. A log-log specification instead delivers a global average. It is exact only if demand truly has constant elasticity. Otherwise, the coefficient is the slope of the linear projection of log consumption on log price, the constant elasticity that best approximates demand over the observed price range in a least-squares sense. The two-regime model is a step-function version of this problem, in which the elasticity takes one value at low prices and another at high prices, and γ measures how much the pooled coefficient leans toward each.

The quality of this approximation depends on the price variation in the data. When prices vary over a narrow range, constant elasticity approximates local behavior well, and the estimate is a reliable summary of responsiveness. When price variation is large or concentrated in specific subperiods, the estimate reflects an average over heterogeneous price environments and is dominated by the periods with the most variation. Literature often relies on exogenous price shocks for identification. These shocks are necessary for credible estimation but also create exactly this large, uneven variation, so the estimated elasticity may not reflect local or typical consumer responses. This matters in energy economics, where elasticities are used to assess policies such as carbon taxes, which operate around normal price levels, and where over- or underestimating responsiveness can change policy conclusions.

In sum, partitioning the sample into price regimes reduces the omitted-variable bias and yields elasticities that are more relevant under stable price conditions. The limits of the log-log model under large or uneven price fluctuations remain, which reflects a trade-off between model simplicity and the ability to capture price-dependent demand responses.

5. 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.

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. When price variation is concentrated in a specific period, as during the energy crisis, this approximation is dominated by the high-price observations and can misrepresent how households respond under normal market conditions. The pooled estimate is not simply an average of the two regime-specific elasticities: because the weight on the high-price elasticity is a regression coefficient (of the regime-specific price term on log price) rather than a share, it can fall outside the range of both, as in our structural break models, where it overstates responsiveness relative to either regime. In the threshold models, it lies between the two regime elasticities and the gap is small, especially for electricity.

Alternatively, accounting for regime-dependent elasticities can give a more informative picture of household energy demand when prices vary substantially. When regimes are defined by the price level, both electricity and gas demand respond significantly at low and high prices, but responsiveness is weaker in the high-price regime, indicating a nonlinear attenuation of price effects. This is consistent with further reductions in consumption becoming harder to achieve as prices rise. When regimes are defined by time, the pattern is different: responsiveness is larger after the onset of the crisis, and for gas it is undetectable before it. Because the crisis coincided with the price surge, this result cannot be separated from other crisis-related factors (such a price salience effect). Taken together, the two specifications show that a single average elasticity masks meaningful variation in how households respond across price environments, and that the type of variation detected depends on how regimes are identified.

This analysis contributes to the literature by highlighting the importance of model specification in environments with large price shocks. Constant-elasticity models remain attractive for their simplicity and interpretability, but their performance depends on how price variation is distributed in the data. When prices fluctuate within a narrow range, the log-log specification approximates local demand behavior well. When price variation is large and concentrated in specific periods, however, the pooled estimate is dominated by those periods and may not describe typical responses. Regime-dependent models then provide a more informative picture of how responsiveness varies across price environments.

More broadly, these findings have implications for policy evaluation and system planning in energy markets. Price elasticities are central to assessing the expected effects of instruments such as carbon taxes or tariff reforms, and to forecasting future energy demand, which is an essential input for grid maintenance and investment. When elasticities are estimated from periods with large exogenous price shocks, the pooled estimate is dominated by those periods and may not describe responses at the price levels where most policies operate. Simulations based on a constant-elasticity assumption may therefore misrepresent how consumers adjust their consumption. Recognizing that elasticity is a local concept, and that it may differ across price regimes, is thus important for interpreting empirical estimates, particularly in episodes of economic turbulence when prices deviate substantially from historical norms.

References:

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.

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

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.

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.

Kudela, P., Havranek, T., Irsova, Z., Kudelova, A., & Sikl, V. (2026). Electricity demand has not become more price-responsive despite ninety years of technological change. Working paper, Charles University, Prague. Available at meta-analysis.cz/electricity.

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.

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. Alternative Functional Form: A Linear Demand Specification.

The baseline analysis relies on a log-log specification that implies a constant price elasticity of demand, and the structural-break model in the main text shows that the elasticity is higher during the energy crisis when prices were on average higher. A possible concern is that this heterogeneity reflects the functional form rather than a change in behavior. To address this concern, we estimate a linear demand specification of the form $C = a + bP + e$.

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, but implied elasticity, b·P/C, rises mechanically with the price level. A linear model could therefore also generate higher elasticities at high prices, without any regime-specific behavior. We assess whether the data favor this alternative by comparing the linear and log-log specifications on the same sample and controls.

	Dependent variable:	
	Volume	
	Electricity	Gas
Price	-2.191***	-24.100***
	(0.110)	(3.874)
Temperature	-8.105**	-43.500
	(3.254)	(48.984)
Daylight	-1.544*	-15.060
	(1.056)	(16.001)
Humidity Index	1.362	-58.023
	(2.515)	(37.816)
Constant	1,711.085*	15,406.772
	(917.702)	(13,904.430)
DSO Fixed Effects	Yes	Yes
Monthly Fixed Effects	Yes	Yes
Observations	2,679	2,026
R2	0.706	0.671
Adjusted R2	0.702	0.666
Residual Std. Error	45.575 (df = 2643)	592.739 (df = 1995)
F Statistic	181.128*** (df = 35; 2643)	135.323*** (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 and gas 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 apply the PE test of MacKinnon, White and Davidson, which tests each specification against the other, using heteroskedasticity-robust standard errors (Table A2).

		Residential Electricity	Residential Gas
RMSE in levels	Linear model	45.3	588.2
	Log-log model	44.2	617.6
PE test p-values (H0=model assumed correct)	H0 linear	<0.001	<0.001
	H0 log-log	0.421	<0.001

Notes: RMSE is computed on a common sample, in kWh per meter, with log-log predictions retransformed using Duan's smearing estimator. Mean consumption is 267 kWh for electricity and 1136 kWh for gas. PE tests follow MacKinnon, White and Davidson (1983), with heteroskedasticity-robust standard errors. For gas, the linear model implies negative fitted consumption for 68 observations, excluded from the test of the linear null.

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

Table A2 reports the RMSE of predicted consumption in levels (kWh per meter) for both models and the PE test results, for the two markets. Lower RMSE values indicate a superior model fit. For the electricity market, the log-log specification fits slightly better than the linear model. This difference is small, but the criterion favors the linear model, since OLS chooses its coefficients to minimize squared errors in levels, which is exactly what RMSE measures. That the log-log model still achieves a lower RMSE in electricity therefore works in its favor. In the gas market, the ranking is reversed: the linear model has a lower RMSE than the log-log model. This gap of about 5% should not be over-interpreted, for the same reason: the lower RMSE of the linear model is less informative, since the criterion favors the linear model by construction. The PE test gives a more informative picture. In the electricity market, it rejects the linear specification ($p < 0.001$) but does not reject the log-log specification. In the gas market, the test rejects both the linear and the log-log specifications ($p < 0.001$), and the linear model implies negative fitted consumption for 68 observations.

Overall, the linear specification is not preferred to the log-log one in either market. In electricity, the data favor the log-log form, and in gas, neither form is adequate. The linear model therefore cannot be presented as a better explanation of the elasticity heterogeneity documented in the main text.

[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.

Since both specifications are rejected in gas, this comparison cannot exclude that functional form matters in that market, and it does not imply that demand is exactly isoelastic. It only shows that the constant-elasticity approximation is at least as consistent with the data as a linear demand function. Evidence that the heterogeneity reflects a change in behavior comes from the structural-break and threshold models in the main text.

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 $\hat{\mathrm{u}}_i = (\hat{u}_{i1}, \hat{u}_{i2}, \dots, \hat{u}_{iT})$. The collection $\{\hat{\mathrm{u}}_1, \dots, \hat{\mathrm{u}}_N\}$ 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

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

where $\hat{y}_{it}^{(0)}$ 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 $\{F_1^*(1), \dots, F_1^*(B)\}$ forms an empirical approximation to the sampling distribution of the test statistic under the null hypothesis. The bootstrap p-value is then computed as

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

[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.

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.

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