When Words Save Watts: Government Communication and Household Electricity Use

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Abstract

A central question for policymakers is whether communication can serve as an effective policy instrument. This paper studies France's 2022–23 energy crisis, when reduced nuclear availability and surging prices led the government to launch one of Europe's largest conservation campaigns. Drawing on more than 12,000 official communications, narrative-specific attention indices from Google searches, and tariff-disaggregated electricity data, the analysis traces the channel from communication to attention to demand. Crisis-framed messages captured attention and reduced consumption, while generic appeals had little effect. Communication thus enhances demand flexibility under scarcity but cannot fully substitute for prices or operational measures.

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1 Introduction

A central challenge in economic policy is how to mobilize households to adjust demand when supply-side flexibility is exhausted. Traditional instruments, such as prices, regulations, or subsidies for new technologies, can be effective, but they often operate with delay and may generate inefficiencies, for instance through deadweight losses arising from imperfect taxation schemes. By contrast, communication and informational appeals can be deployed rapidly and at low fiscal cost, offering policymakers an additional lever when time and resources are constrained. The effectiveness of such instruments, however, remains uncertain. Although existing research has shown that consumer attention is limited, most empirical evidence derives from small-scale interventions or randomized experiments. Whether large-scale government communication can durably alter household behavior in real-world crises therefore remains an open question

This paper precisely fills this gap as it focuses on France and exploits the natural experiment provided by the European energy crisis of 2022-2023. Triggered by a combination of geopolitical tensions, including the curtailment of Russian gas imports, and technical constraints such as the temporary shutdown of nuclear reactors, the crisis placed unprecedented stress on the French electricity system. Wholesale prices surged, public concern over potential winter power failures intensified, and national attention shifted toward electricity consumption. Household demand represented one of the few margins of rapid adjustment available to maintain system balance. Reducing load at critical times directly enhances security of supply and lowers the risk of blackouts, while also limiting reliance on gas and coal-fired plants that are typically dispatched when demand peaks. In response to this situation, the French government launched a nationwide communication campaign urging citizens to reduce their energy use. These efforts ranged from televised appeals to sustained messages promoting low-cost conservation measures, such as lowering indoor temperatures to 19°C. Simultaneously, the Minister for Energy Transition authorized the national grid operator to implement remote load control on households equipped with specific electric heating systems. This intervention temporarily reduced electricity consumption during peak demand periods, directly limiting these households capacity for voluntary adjustment.

The goal of this paper is twofold: first, to quantify whether government communication in times of crisis can alter household electricity demand, and second, to trace the mechanism linking communication to consumption through its impact on public attention. Two distinct narratives are examined. The first, energy crisis communication, emphasizes scarcity and system reliability, seeking to mobilize urgent behavioral responses. The second, energy conservation communication, aims to encourage more sustained adjustments. Distinguishing between these narratives is central: while both featured prominently during the crisis, theory and prior evidence suggest that urgency-driven framing captures attention more effectively than generic conservation appeals, with potentially different implications for household behavior.

The identification strategy builds on the idea that wholesale electricity prices influence household demand through two distinct channels in France. The first, an institutional channel, operates through the national regulated retail tariff, which adjusts only with long lags, typically six months or more, and may be decoupled from wholesale prices through ministerial interventions such as the 2022–2023 tariff shield. A second, faster channel is hypothesized to run through government communication and Public Service Announcement (PSA): sharp increases in spot prices are followed by crisis and conservation oriented messages that shape public attention and, potentially, household behavior within weeks. The empirical analysis tests for the existence and magnitude of this attention channel alongside the slower institutional pass-through.

A three-step empirical strategy is used to identify the chain from government communication to household electricity demand. First, more than 12,000 official statements were collected from the government's central website, which records all speeches and media appearances by government members. A semi-supervised machine learning algorithm was then used to classify these communications by narrative type, producing daily measures of communication intensity. In addition, the INA Lab helped retrieve the daily number of PSA from the televisual campaign lunch during the winter 2022-2023.[1] Second, the link between these narratives and public attention is established by combining the communication series with Google Search Volume (GSV), using a reduced-form model to separate conservation and crisis signals. Third, the impact of narrative-specific attention on household electricity use is estimated using a time-series framework that exploits the daily frequency of the data. The high-frequency setting is crucial: while policy interventions occurred simultaneously during the crisis, communication shocks materialised within days, whereas retail price adjustments and temperature effects evolved more slowly or seasonally. By controlling for these slower-moving confounders and for load-control interventions, the design isolates the short-run link from attention to consumption. This sequential design traces the mechanism from communication to attention and, ultimately, to consumption.

The empirical results highlight two main findings. First, the analysis of attention dynamics shows that public interest in conservation messaging emerges primarily when such messaging is embedded within a broader crisis narrative, and when televised campaigns are broadcast. In contrast, attention to crisis-related communication responds directly to salient concerns about system reliability and peaks during periods of intense media coverage about potential shortages. This pattern indicates that the salience of conservation behaviors is conditional on being framed within a context of scarcity, whereas crisis narratives can capture attention independently.

Second, the consumption analysis shows that attention accounted for up to 14% of the reduction in electricity use, and that this effect would likely have been larger absent the load-control interventions that curtailed available flexibility. Price and temperature variations nevertheless exert the largest and most persistent influence on household electricity demand, particularly among households on Peak/Off-Peak tariffs. Taken together, these findings suggest that while communication can mobilize attention, its translation into behavioral change depends critically on both narrative framing and the institutional constraints that shape demand-side flexibility.

This paper main contribution is to provide rare evidence on the effectiveness of government communication in shaping household electricity demand in a real-world crisis, complementing a literature that has largely relied on controlled experiments (see for example the

[1] The Institut national de l'audiovisuel (INA) is France's national audiovisual archive and research institution.

literature review by Buckley (2020)). In particular, this paper contributes to the emerging literature on large-scale natural experiments linking conservation incentives, public attention, and consumption outcomes. He and Tanaka (2023) study post-Fukushima Japan, where the shutdown of all nuclear power plants prompted conservation efforts that unintentionally increased mortality during heat waves. In the European energy crisis context, Jamissen et al. (2024) examines the channel from public attention, measured via Google Searches, to gas consumption, while Behr et al. (2025) exploits a difference-in-differences design comparing households with and without price variations to assess how conservation incentives shaped gas demand. Yet neither study investigates the full process from conservation incentives through public attention to consumption. This paper fills that gap by focusing on electricity, leveraging consumption data disaggregated by tariff structure to analyse how conservation incentives and crisis narratives jointly shaped demand under heterogeneous pricing schemes.

The results carry broader implications for the design of demand-side policy. Informational campaigns are most effective when they coincide with systemic shocks that heighten public concern, and their impact is concentrated among consumer segments with sufficient discretionary flexibility. This suggests that communication should be viewed as a complement, rather than a substitute, to price incentives and operational tools. More generally, the findings underscore the role of public narratives in shaping household behavior under conditions of scarcity, whether in energy, water, health, or fiscal compliance. Designing communication strategies that are credible, well timed, and targeted thus becomes a central challenge for policymakers seeking to mobilize household responses during periods of stress.

The remainder of this paper is organised as follows: in Section 2, energy conservation and associated incentives are defined. Section 3 presents how the energy crisis triggers different types of energy policies. Then, Section 4 presents the sources, pre-processing and description of datasets used for this empirical study. Section 5 presents the empirical methodology. Section 6 presents the main results and Section 7 discusses the main results.

2 Definitions and Literature around Energy Conservation at Home

The latest IPCC report defines the concept of sufficiency as *policies, measures, and daily practices that avoid the demand for energy, materials, water, and land while delivering human well-being for all within planetary boundaries* (Shukla et al., 2022). In the residential sector, sufficiency regarding at home energy use is usually referred to as energy conservation. It seeks to reduce final energy use through changes in habits, behaviors, and consumption patterns, rather than through technological improvements alone.[2] This paper adopts the language of conservation, as the empirical setup does not allow for assessing broader implications for planetary boundaries.

The distinction between energy efficiency and energy conservation is essential to frame the discussion. Energy efficiency refers to the adoption of technologies that reduce energy

[2](See for exp. Richler, 2016; Jachimowicz et al., 2018; Myers and Souza, 2020; Bonan et al., 2021; Knittel and Stolper, 2021; Caballero and Ploner, 2022; Loschke et al., 2024)

consumption while maintaining the same level of service. It typically improves the ratio of energy used per unit of service delivered. However, it is often constrained by the energy paradox i.e the under-adoption of seemingly profitable efficiency investments (Jaffe and Stavins, 1994), and by rebound effects, where energy savings are partially offset by the need for an increase in comfort (Sorrell et al., 2007; Peñasco and Anadón, 2023).

By contrast, energy conservation involves behavioral adjustments that deliberately reduce energy use. It typically addresses curtailment behaviors, where users consciously lower their consumption in response to incentives, constraints, or information campaigns (Gardner and Stern, 1996). Conservation is thus in theory less exposed to rebound effects and plays a critical role in demand-side management.

In a formal economic framework, List et al. (2023) conceptualize behavioral biases as internalities, systematic errors in how agents perceive the marginal benefits or costs of consumption. These internalities often stem from overlooked co-benefits, poor information, or limited awareness of the broader consequences of consumption choices. In this context, energy conservation incentives can be interpreted as mechanisms that reduce these internalities, by providing information, setting goals, or reshaping social norms. This theoretical perspective aligns with earlier research suggesting that individuals often lack sufficient information to engage in optimal energy-saving behaviors, and that acquiring such information can be costly (Allcott and Mullainathan, 2010; De Young, 2000; Hungerford and Volk, 1990; Schultz et al., 2002). Behavioral incentives are therefore particularly potent during crises, as crisis framing acts as a salience amplifier in an information-rich environment where attention is scarce (Kudesia and Lang, 2024). When messages emphasize imminent risks, such as power shortages or blackout probabilities, they cut through competing stimuli, elevate issue salience, and trigger rapid information seeking and behavioral vigilance (Curotto et al., 2025; Spence et al., 2021). This is consistent with classic attention-economics logic and media-effects research on framing/agenda-setting (Dyer and Kolic, 2020; Scheufele and Tewksbury, 2007; Wicke and Bolognesi, 2020).

While theoretical arguments support the effectiveness of conservation incentives, the empirical evidence reveals considerable heterogeneity in their actual impact. Several meta-analyses have attempted to classify conservation incentives and explain variations in their effectiveness (Abrahamse et al., 2005; Andor and Fels, 2018; Blasco and Gangl, 2023; Delmas et al., 2013; Brandon et al., 2017).

Building on these reviews, four broad categories of incentives emerge: Monetary incentives, which aim to align consumption behaviors with financial self-interest by making costs and potential savings more salient. These incentives tend to be more effective when the potential gains are significant (Delmas et al., 2013). Goal-setting interventions, which involve setting specific consumption targets (e.g., "reduce your consumption by 10%"). While goal-setting alone shows limited effectiveness, its impact increases substantially when combined with feedback mechanisms (Abrahamse et al., 2005; Andor and Fels, 2018). Feedback incentives, which provide information about energy use. Feedback can relate to past consumption, real-time consumption, or comparative consumption relative to peers. Comparative feedback, leveraging social norms, is found to be the most effective (Delmas et al., 2013). Information strategies, which disseminate energy-saving tips. Low-involvement strategies (e.g., mass media campaigns, general workshops) have limited behavioral impact, while high-involvement strategies (e.g., personalized advice after a home energy audit) are more successful (Gonzales et al., 1988; Winett et al., 1982). Table 1 summarizes these different categories and their relative effectiveness, based on existing meta-analyses. Quantitatively, Buckley (2020) estimates that earlier reviews suggested energy savings of around 7% could be achieved through informational incentives. However, using a stricter selection of more recent experimental studies, she argues that a more realistic expectation is a reduction of 2–4% in energy consumption. Beyond the classification of incentives, another important issue is the persistence of effects. Allcott and Rogers (2014) emphasize that the effects of behavioral interventions often decay over time unless reinforced. Their work highlights the importance of repeated interventions initially, to help individuals form new habits, before reducing intervention intensity once behaviors are stabilized.

Table 1: Incentives promoting energy conservation at home

Incentive Type	**Details**
Monetary	*Definition*: Incentives about potential monetary savings *Effectiveness*: Effective *if* the expected monetary gain is large
Goal Setting	*Definition*: Energy saving commitment to a concrete reference point *Effectiveness*: Effective *if* combined with feedback mechanisms
Individual Feedback	*Definition*: Personalised information about past energy consumption *Effectiveness*: Effective
Peer Feedback	*Definition*: Personalised information about energy consumption by peers *Effectiveness*: Effective
High Involvement Information Strategy	*Definition*: Personalised energy-savings tips *Effectiveness*: Effective *because* very personal
Low Involvement Information Strategy	*Definition*: General energy-savings tips *Effectiveness*: Ineffective *because* too generic

Notes : This classification is build upon the following literature (Abrahamse et al., 2005; Andor and Fels, 2018; Blasco and Gangl, 2023; Delmas et al., 2013)

While the topic feels recent to many policymakers, incentives for energy saving are not new. On 2 February 1977, during the oil crisis, President Jimmy Carter gave a televised speech urging Americans to lower their thermostats to 65°F (18°C) during the day and 55°F (13°C) at night to save natural gas. Following this announcement, Luyben (1982) assessed the effectiveness of the televised appeal and found no significant difference in thermostat settings between those who had heard the message and those who had not. More broadly, several studies in the late 1970s and 1980s investigated the effectiveness of conservation incentives (Craig and McCann, 1978; Hutton and McNeill, 1981; Walker, 1980).

In France, conservation campaigns have also been launched repeatedly since the first oil shock of 1973. Initially motivated by energy security concerns, the Ministry of Energy and the newly created *Agence pour les Économies d'Énergie* (AEE) promoted reduced heating and efficiency measures. The most emblematic slogans were *"En France on n'a pas de pétrole mais on a des idées"* ("In France we don't have oil, but we have ideas") (1976) and the *"Chasse* *au gaspi"* ("Hunt for waste") of the early 1980s. With the rise of climate concerns and the Kyoto Protocol, conservation returned to the policy agenda in the late 1990s. The *Agence de l'environnement et de la maîtrise de l'énergie* (ADEME), created in 1990, launched new national campaigns, most notably *"Économies d'énergie, faisons vite, ça chauffe !"* ("Energy savings, let's move fast, it's getting hotter") (2004–2006), which framed conservation as both an environmental necessity and a means of reducing household costs. Unlike these earlier efforts, typically mediated by specialized agencies such as ADEME, the 2022–2023 campaign was spearheaded directly by the government at the highest political level. This shift reflected both the severity of the crisis and the need for rapid, visible coordination, making it one of the largest conservation appeals ever conducted in Europe.

During the 2022–2023 European energy crisis, several studies have provided early empirical insights into behavioral adjustments. Doumèche et al. (2023) document shifts in energy consumption patterns in France, notably linked to increased remote working and household-level conservation efforts. Ruhnau et al. (2023) show that households and firms across Europe adopted energy-saving behaviors such as lowering thermostat settings and adapting production processes. Finally, Jamissen et al. (2024) and Behr et al. (2025) find that in Germany a significant share of natural gas demand reduction was driven by heightened public concern over the energy crisis, underscoring the role of political and media narratives. Relatedly, He and Tanaka (2023) report that in Japan after 2012, a large part of electricity demand reduction was linked to heightened public concern over blackout risks following the nuclear shutdown.

3 Background

The European energy crisis of 2022–2023 revealed the fragility of energy supply systems in the face of geopolitical and climatic shocks. In France, the convergence of reduced Russian gas supplies, a sharp increase in spot market energy prices, and declining nuclear generation capacity generated acute pressure on electricity markets.[3] As documented by the French Energy Regulatory Commission (CRE), these tensions led to unprecedented increases in regulated electricity tariffs, which threatened household purchasing power despite traditionally stable prices in the French context.

In response to the energy crisis, the French government adopted two distinct yet complementary main policy instruments. First, it launched a national conservation campaign, the *Plan de Sobriété Énergétique* ("Energy Conservation Programm"), designed to promote voluntary reductions in energy use through informational appeals. Second, it implemented a price shield mechanism to mitigate the impact of rising wholesale prices on household electricity bills (see details in Appendix Table 8). While the latter limited the full pass-through of market price increases, regulated tariffs nevertheless rose over the period, preserving at least

[3]At the time, France's nuclear fleet had been severely constrained by extended maintenance and stress corrosion issues, driving nuclear output to its lowest level in decades. As of late 2022, nearly half of the approximately 56 reactors were offline, reducing significantly annual production, according to the annual report from the French Energy Regulatory Commission.

partial incentives for demand reduction. This combination of policies, protecting households from the sharpest price shocks while simultaneously encouraging behavioral adjustments, reflects a deliberate strategy to balance affordability concerns with energy security objectives. Rather than being contradictory, the joint deployment of monetary and non-monetary levers illustrates the government's attempt to manage crisis-induced demand pressures without undermining public support.

The energy conservation program was formally launched on 6 October 2022, but the first political signals emerged as early as February 2022, when President Emmanuel Macron elevated energy conservation to a national policy objective.[4] By June 2022, the government had announced a goal of reducing energy consumption by 10% by 2024, initially targeting public administration, the industrial sector, and services. This objective was expanded to include all firms and households in September 2022. The official launch of the Plan was accompanied by a detailed press kit outlining conservation goals and energy-saving practices, as well as the deployment of the national communication campaign called *Chaque geste compte*, disseminated across television, radio, and social media.[5]In parallel, numerous members of the government consistently promoted energy conservation during their public appearances.

In addition to these non-monetary measures, the French government implemented direct price protection through a shield price mechanism. At the end of 2021, facing a proposed increase of 44.5% excluding taxes in residential tariffs, the government acted swiftly. The *Domestic tax on final electricity consumption* (TICFE) was drastically reduced to 1€/MWh for all consumers. Retail price increases were then capped at 4% including taxes in February 2022. This capping policy was maintained during subsequent tariff revisions in July 2022, January 2023, and June 2023.

A third intervention, which was more discreet, involved direct control of residential electricity consumption. For around 4 million households with Peak/Off-Peak contracts and *pilotable* hot water systems, the government authorised grid operators to remotely deactivate the heating system controller during midday. These 4 million households represented around 28% of the total number of Peak/Off-Peak contracts on average over the study period (14 million contracts). This control was implemented in two consecutive winter seasons, October 2022 to April 2023 and November 2023 to March 2024, and limited to a maximum of two hours per day between 11:00 and 15:30, with the interruption starting before 14:00.[6]

4 Data

4.1 Data Sources

Data on residential electricity consumption are obtained from the *Enedis* Open Data, operated by France's main electricity distribution system operator. Enedis, a regulated subsidiary of Électricité de France (EdF), manages the low- and medium-voltage grid covering roughly

[4]Statement by Mr Emmanuel Macron, President of the French Republic, on energy policy, in Belfort on February 10, 2022.

[5]Campaign materials are available at `https://shorturl.at/SBEGM`

[6]See official decrees: `https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000046331146` and `https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000048063360`

95 percent of households in mainland France, with the remainder served by local municipal distributors. Temperature is drawn from the *European Centre for Medium-Range Weather Forecasts* (ECMWF). Price data combine two sources: regulated retail tariffs provided by the *Energy Regulatory Commission* (CRE) and day-ahead wholesale electricity prices retrieved from the ENTSO-E Transparency Platform. To measure government communication, the study compiles more than 12,000 official statements from the *Vie publique – Au cœur du débat* public repository, which archives all public speeches by French government members. These are combined with daily *Google Search Volume* indices for energy-related terms, which proxy public attention over time.
Table 6 in Appendix B summarises all data sources, frequency, and coverage.

4.2 Residential Electricity Consumption

This study relies on daily electricity consumption data for residential customers provided by Enedis, the main distributor of low-voltage electricity in France. Enedis publishes aggregated data, distinguishing between residential and professional users, allowing a focused analysis of household consumption patterns. The dataset captures the actual daily electricity usage of residential consumers under contract with Enedis, offering comprehensive coverage of the French residential electricity sector. The dataset covers a period from 1 July 2019 to 30 June 2024, providing five complete years of high-frequency observations. For consistency across heating seasons, years are defined as energy years, running from July to July so that each observation window fully encompasses a winter period. For instance, the year 2022 spans from 1 July 2022 to 30 June 2023, covering the entire winter of 2022–2023. This structure ensures that interannual comparisons of consumption patterns are not biased by incomplete heating seasons and that policy interventions occurring during the cold months are consistently captured within a single analytical year.

Residential consumers are divided into two main tariff profiles: Base and Peak/Off-Peak. Table 5 illustrates the annual electricity consumption patterns for these two profiles. Households with Off-Peak contracts, who benefit from lower period rates, exhibit significantly higher electricity consumption compared to Base profile households, whose average annual consumption is only about half that of Off-Peak users. When comparing electricity consumption between the pre-crisis reference period (2019–2021) and the crisis years (2022–2023), a marked reduction is observed. Overall, residential consumption decreased by 10.7 TWh. This reduction is entirely driven by households with Off-Peak contracts, who reduced their consumption by 12.7 TWh. In contrast, Base profile consumption decreased slightly by -1.1 TWh over the same period. When data are expressed in terms of consumption per contract (in MWh/contract/year rather than total TWh), a more nuanced picture emerges. After adjusting for the 2% increase in the number of Base contracts between 2021 and 2023, Base profile households show a higher decline in consumption. Specifically, the reduction amounts to -0.9 MWh/contract/year for Off-Peak households and -0.1 MWh/contract/year for Base households. This observation highlights the importance of normalising consumption by the number of contracts to accurately interpret variations across profile types. Using aggregate consumption data alone would obscure part of the behavioural change among Base profile households. By relying on per-contract measures, the analysis yields more meaningful insights into how different tariff profile groups responded to the crisis environment and policy interventions.

Table 2: Average Annual Electricity Consumption

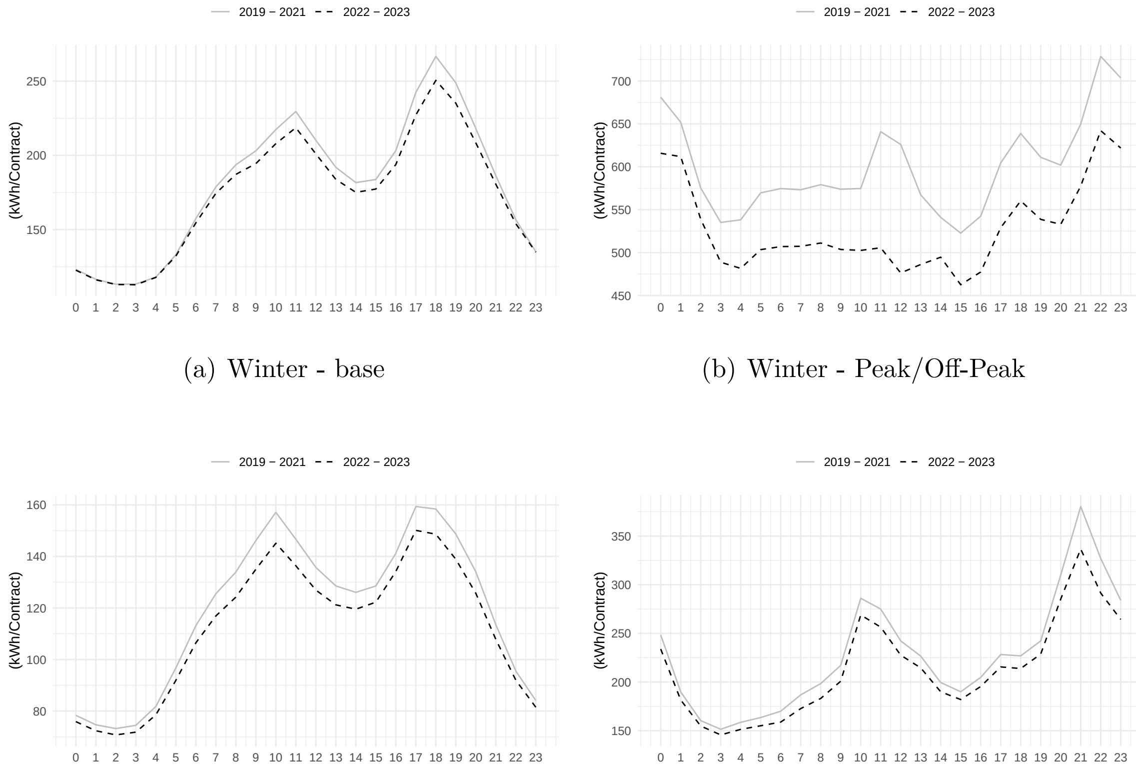
Panel A. Total electricity consumption (TWh)				
	2019–2021	2022–2023	Difference	%
Base	51.0	49.9	-1.1	-2.3
Peak/Off-Peak	97.7	85.0	-12.7	-13.0
Total	124.8	114.1	-10.7	-8.6
Panel B. Average consumption per contract (MWh/contract)				
	2019–2021	2022–2023	Difference	%
Base	2.9	2.8	-0.1	-3.8
Peak/Off-Peak	6.8	5.9	-0.9	-12.5
Total	8.1	7.3	-0.8	-10.2

Notes : Years are defined from July to July in order to encompass one winter period per year of study. Thus, the year 2022 goes from July 2022 to June 2023.

To go further on the description of residential electricity during the period, Figure 1 presents the average hourly electricity consumption per contract during winter months for households on and Peak/Off-Peak tariffs. The goal is to visualise the effect of load control during middays, thus different periods are presented: the pre-crisis winters (2019–2021), and the first intervention winter (2022-2023). Let us recall that during winter 2022/2023 and winter 2023/2024 grid operator managed at distance heating water system for over 4 millions housing. Peak/off-peak households display a marked drop in midday consumption during the intervention period. Between 11:00 and 14:00, the load curve for 2022-2023 shows a distinct downward shift relative to the pre-intervention baseline, consistent with the remote deactivation of water-heating systems during this period. The reduction is sharpest between 12:00 and 14:00, corresponding closely to the maximum two-hour control window authorised under the policy.
This visual evidence strongly suggests that the load-control measure explains the reduced consumption during the targeted hours without significantly shifting demand to adjacent hours. The difference between Base and Peak/Off-Peak profiles reinforces the interpretation that the observed midday reduction is directly attributable to the hot-water control policy, since Base-tariff households were not subject to the intervention. For comparison, the same daily load profiles are shown for the summer months. As expected, the patterns lack the midday dip observed in winter, reinforcing once more the idea that the reduction between 11:00 and 14:00 during winter is specifically associated with the controlled deactivation of hot water systems rather than an individual shift in consumption.

4.3 Retail Tariff

Daily data on retail electricity prices for residential consumers are not available in France. However, given that approximately 76% of residential customers are subject to the regulated



(a) Winter - base

(b) Winter - Peak/Off-Peak

(c) Summer - base

(d) Summer - Peak/Off-Peak

Figure 1: Average hourly load by season and tariff profile

electricity tariff (*tarif réglementé de vente*, TRV) (CRE, 2024), this study relies on available bi-annual TRV data to approximate the evolution of retail prices.

The residential sector is characterized by different tariff profiles, primarily distinguished by the contractual options for electricity pricing. Table 3 Panel A presents the average daily distribution of contracts for the period 2019-2024, across tariff profiles and subscribed power levels based on the Enedis database used in this study. The Base tariff profile accounts for 54% of residential contracts, while the Off-Peak profile represents 45%. The most common configuration is the Base profile with a 6 kVA subscription, followed by the Off-Peak profile with the same subscribed power. Together, these two tariff and power combinations represent around 59% of all contracts in the database. In contrast, the tempo profile, characterized by variable pricing based on daily color-coded signals, accounts for only 1% of contracts. Table 3 Panel B presents the average daily distribution in terms of electricity consumption for the period 2019-2024, across tariff profiles and subscribed power levels. The Base tariff profile accounts this time for 34% of residential consumption, while the Off-Peak profile represents 64%. The strongest consumption comes from Off-Peak profile with a 9 kVA subscription, followed by the Base profile with a 6 kVA subscription. Together, these two tariff and power combinations represent around 39% of total consumption. Once again the tempo profile, accounts for less than 2% of consumption. Due to its complex pricing structure and limited representation in the data, tempo contracts are excluded from the analysis.

Table 3: Distribution of Residential Electricity Contracts and Consumption

Panel A. Share of Residential Contracts (%)										
	Contracted Power (kVA)									
	3	6	9	12	15	18	24	30	36	Total
Base	4.46	**39.73**	7.33	1.96	0.30	0.37	0.05	0.02	0.06	**54.28**
Peak/Off-Peak	–	**19.16**	15.81	6.70	1.00	1.66	0.16	0.05	0.12	44.66
Tempo	–	–	**0.70**	0.16	0.03	0.15	–	0.01	0.01	1.06
Total	4.46	**58.89**	23.84	8.82	1.33	2.18	0.21	0.08	0.19	100.00
Panel B. Share of Residential Electricity Consumption (%)										
	Contracted Power (kVA)									
	3	6	9	12	15	18	24	30	36	Total
Base	1.08	**21.24**	7.07	3.06	0.54	0.97	0.19	0.08	0.33	34.56
Peak/Off-Peak	–	17.60	**24.94**	13.45	2.28	3.97	0.67	0.24	0.64	**63.79**
Tempo	–	–	**0.86**	0.31	0.06	0.32	–	0.06	0.04	1.65
Total	1.08	**38.84**	32.87	16.82	2.88	5.26	0.86	0.38	1.01	100.00

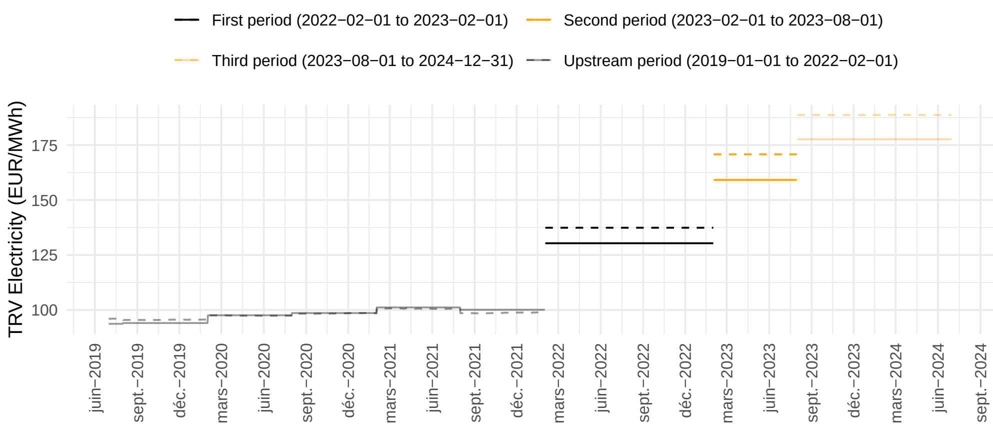
Notes : Panel A reports the share of residential electricity *contracts* by tariff type and contracted power (kVA). Panel B reports the corresponding share of total *electricity consumption.* Bold values indicate the modal power level within each tariff profile. Dashes (–) denote non-applicable combinations of tariff and contracted power.

To build consistent price series for empirical analysis, two weighted tariffs are constructed: one for households with a Base profile and another for households with a Peak/Off-Peak profile. The underlying data for this construction are the set of 18 TRV tariffs provided by the CRE, corresponding to different combinations of profile and subscribed power levels. The weighting is based on the observed distribution of contracts in the Enedis database (see Appendix B Table 7 for the yearly rate change of contracts by profile). The weighted tariff at day t, denoted $P^w_{i,t}$, is calculated according to the following formula:

$$P^w_{i,t} = \frac{\sum_{i=1}^n P_{it} \times w_{it}}{\sum_{i=1}^n w_{it}} \tag{1}$$

where P_{it} is the tariff for profile and power i at time t, and w_{it} is the weight reflecting the proportion of consumption corresponding to that tariff. This methodology enables the construction of two bi-annual weighted tariffs that accurately reflect the market structure for baseand Off-Peak customers.

Figure 2 presents the resulting tariffs paid for both Base and Off-Peak profiles. In particular, the tariff can be seen as four different pricing blocks or periods. The first one goes from 2019-01 to 2022-02 and is defined as the upstream period, where prices were usually flat. Then a first increase arrived in 2022-02, increasing the tariff by around 4%, then a second and a third more pronounced increases, in 2023-02 and 2023-08.



Notes : The solid line represents the Peak/Off-Peak profile, and the dashed line represents the baseprofile.

Figure 2: Tariffs for baseand Peak/Off-Peak profiles

4.4 Government Communication

To capture the energy communication issued by the French government during the 2022–2023 energy crisis, a new textual corpus has been constructed, focusing on government speeches and official communications.[7] This approach is motivated by the need to assess two distinct narratives: communication promoting energy conservation, and communication emphasising the risks linked to the energy crisis, with the idea that narratives around scarcity can trigger behavioural change (Curotto et al., 2025; Spence et al., 2021; Jamissen et al., 2024; Loschke et al., 2024; He and Tanaka, 2023).

The corpus is built using the public speeches collection (*Collection des discours publics*) available on the French governmental platform www.vie-publique.fr. This collection brings together over 160,000 speeches delivered by prominent political figures: presidential speeches since 1974, speeches by the Prime Minister and government members since the early 1980s, and communications from the Council of Ministers since 1974. For the purposes of this study, all communication published between January 2019 and December 2024 have been systematically scraped. After initial cleaning and formatting, the corpus comprises a total of 12,184 documents. Each document contains data and metadata such as the title, the date of delivery, the speaker's name and position, and the full text of the statement.

To systematically analyze government communication in promoting residential energy savings during the 2022–2023 crisis, it is essential to quantify the flow and intensity of relevant public communication over time. Given the scale of the corpus and the diversity of political discourse, manual labeling alone would be impractical. Therefore, a classification strategy is developed to automatically identify and track government communication encouraging

[7] A potential limitation of this approach is its exclusive focus on communication from the executive branch and government officials, without considering communications from opposition parties. However, during the energy crisis, there was broad political consensus across party lines regarding the urgency of implementing energy savings measures.

energy savings. The classification task is formulated as a binary prediction problem. For each statement in the corpus, the goal is to assign a label $y_i = 1$ if the text promotes energy savings under a studied narrative, either conservation or crisis, and $y_i = 0$ otherwise. The input variables include: the cleaned full text of the speech; the title of the speech and the name of the speaker. Labels are initially assigned through keyword matching: speeches explicitly mentioning energy conservation (*sobriété énergétique*) or energy crisis concerns (*crise énergétique*) are labeled $y = 1$; speeches focused on unrelated topics (e.g., elections, vaccines) are labeled $y = 0$; and remaining speeches are treated as unlabeled data. The full methodology to train the classification model, based on a semi-supervised XGBoost algorithm, is detailed in Appendix E.

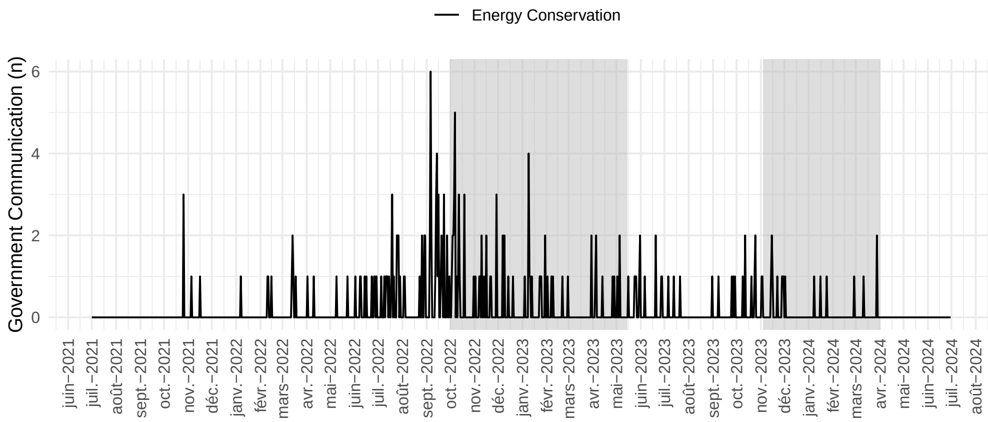
The final classified data are then used to construct time series that count at each day communication identify to either of the narratives, as presented in Figure 3, next to the day-ahead electricity spot prices for France. The correlation between spot price increases and government communication is evident, inducing the identification hypothesis that spot prices drive government communication as the market signal takes time to appear in the regulated tariff. Communication for energy conservation emerges first, peaking on September 6, 2022. Subsequent spikes in summer 2023 and winter 2024 once again align with the State's recurring seasonal media campaigns aimed at promoting energy-saving behaviours. Government communication around the energy crisis peaks later, on September 1, 2023, however, the distribution of both communications seems to be very close starting in October 2021.

Relying solely on the raw daily count of classified communication would probably be insufficient to capture the real behavioural stimulus, as it is unlikely that a single isolated statement triggers an immediate and significant response in residential attention to the narratives (Allcott and Rogers, 2014). Thus, an indicator is constructed to proxy for the *buzz* given to energy savings relative to the total political communication. Similar approaches are found in the monetary policy literature, where the effectiveness of ECB communication has been shown to depend not just on the number of announcements, but also on their intensity, prominence, and cumulative visibility. For example, Istrefi et al. (2025) documents that inter-meeting speeches and interviews by ECB Governing Council members move markets nearly as much as formal policy announcements, underlining the importance of communication volume and timing. Likewise, Jarociński and Karadi (2020) shows that the market impact of ECB communication depends on the frequency and clustering of messages, while Berger et al. (2006) develops a systematic index of communication tone to capture how repeated and salient statements shape expectations. These studies motivate the use of "buzz" metrics to capture the cumulative and amplifying effects of political communication on public attention.

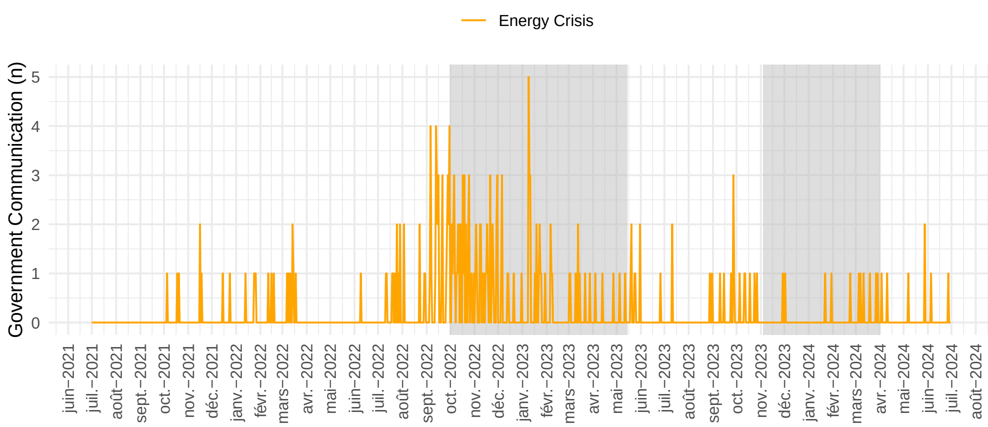
This paper "buzz-weighted" metric (g_{kt}) is defined in equation 2.

$$(g_{k,t,n}) = \underbrace{\frac{1}{n}\sum_{0}^{n-1}}_{\text{Cumulative}} \underbrace{(\frac{1}{N_{t-j}}\sum_{i=1}^{N_{t-j}} \omega_i g_{kti})}_{\text{Buzz}} \tag{2}$$

With $g_{k,t,n}$ representing the presence of topic k in the i-th statement on day t, N_t is the total number of communications on day t, and ω_i is a weight reflecting the prominence



(a) Energy Conservation



(b) Energy Crisis

Figure 3: High-frequency government communication from Public Collection

of the statement. To construct a robust index of government communication, alternative specifications are generated by combining moving-average windows with different weighting schemes. Eleven windows, ranging from 1 to 90 days, are applied to three metrics: the raw count of messages, a buzz index with uniform weights, and a buzz index with weights based on whether the term appears in the title or the type of communication (e.g., interview). This yields 33 candidate measures, from which the optimal specification is selected using the Akaike Information Criterion (AIC), balancing fit and parsimony.

4.5 Public Service Announcement

Public interest advertising (PSA) refers to government-sponsored communication campaigns designed to promote socially desirable behaviours rather than commercial outcomes. In

France, such campaigns are coordinated by public agencies or ministries and disseminated through major media channels at no or reduced cost. Unlike commercial advertising, PSAs pursue non-market objectives such as improving health, safety, or energy conservation. Legally, they are classified as non-commercial messages under the French broadcasting framework and may be aired outside ordinary advertising quotas, provided they respect general content restrictions on decency, truthfulness, and political neutrality. Economically, these campaigns serve as a low-cost policy lever to influence individual behaviour when direct regulation, taxation, or price signals are insufficient or politically costly. Their effectiveness depends on attention formation, salience, and social norm mechanisms rather than pecuniary incentives, positioning them at the intersection of behavioural economics and public policy.[8]

The Institut national de l'audiovisuel (INA) is France's national audiovisual archive and research institution, established to preserve and provide access to the country's radio and television heritage. Beyond its archival mission, INA develops digital tools and datasets that enable quantitative analysis of media content through its research platform, INA le Lab, which facilitates academic access to annotated audiovisual corpora. For the present study, data on the energy conservation campaign were retrieved with the help of this data lab center, this provides a comprehensive measure of campaign intensity and exposure over time.[9]

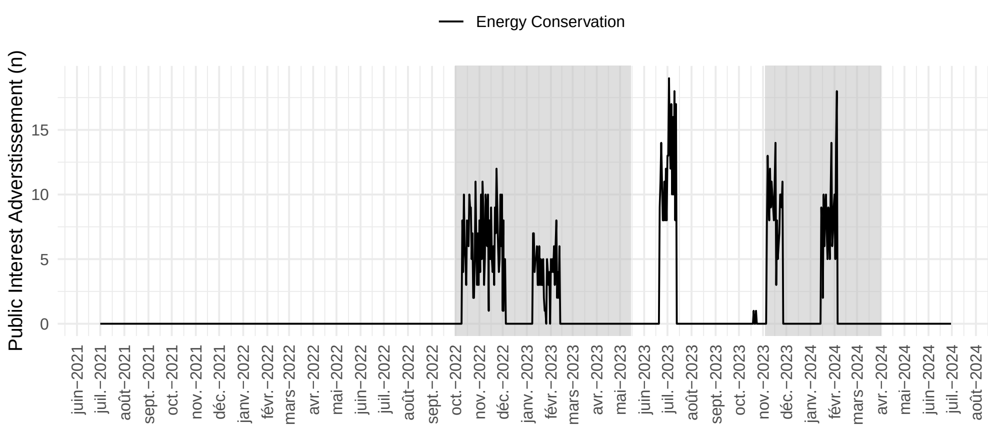


Figure 4: High-frequency Public Service Announcement about Energy Conservation

Figure 4 presents the daily number of Public Service Announcements (PSA) related to energy conservation aired on national television. The campaigns were organized in distinct waves, with three main periods of activity: two major winter campaigns running from October to March during the 2022–2023 and 2023–2024 heating seasons, and a summer campaign in July 2023. The synchronization between these campaigns and the load-control interventions implemented by the grid operator is striking. The PSA waves during winter precisely coincide with the periods when midday water-heating systems were remotely curtailed, suggesting that

[8]Law no. 86-1067 of 30 September 1986, relating to freedom of communication, which establishes the general framework for audiovisual communication in France.

[9]INA le lab. Accessed on 02/10/2025 at https://doi.org/10.58079/12yb1

mass-media conservation appeals and direct operational measures were jointly deployed to sustain public engagement and stabilize electricity demand.

4.6 Google Search Volume

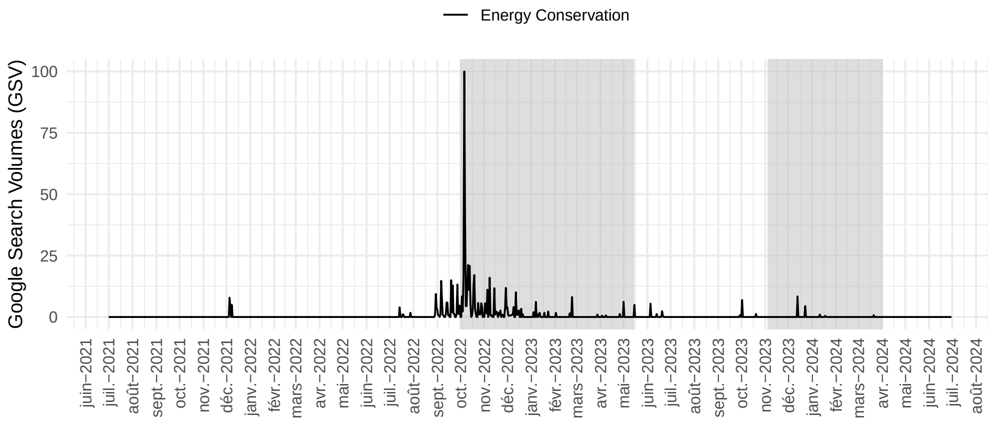
To measure public attention to energy savings narratives, daily Google search volumes (GSV), commonly known as Google Trends, are used initially for the search terms "*sobriété énergétique*" (energy conservation) and "*crise énergétique*" (energy crisis). Indices are then constructed using sets of related search queries rather than single keywords. For the energy conservation narrative, the set includes *sobriété énergétique*, *plan de sobriété énergétique*, and other closely related terms (Table 11, Panel A). For the energy crisis narrative, the set includes *crise énergétique*, *crise énergétique européenne*, and similar variations (Table 11, Panel B). This aggregation procedure mitigates measurement noise from idiosyncratic spikes in single search terms and yields a broader, more stable proxy of digitally expressed public attention. Google Search Volume indexes capture the relative search intensity of a given term, normalized to a 0–100 scale within each queried period. While Google Search Volume has become a popular tool in applied economics to approximate attention, particularly during crises and policy shifts, it presents technical limitations for constructing consistent long-run series notably due to the 90-day cap for daily frequency queries and the internal rescaling of values across time windows (Da et al., 2013; Eichenauer et al., 2022). [10] It is important to note that Google Search Volume captures search behaviour only among internet users. In the French context, this likely under-represents older or rural households with lower internet usage, and over-represents younger, urban, and more digitally connected groups. As such, the measure should be interpreted as reflecting digitally expressed attention rather than the full distribution of public awareness.

Figure 5 presents the Google Search Volume indices capturing household attention in France to the narratives of energy conservation and energy crisis. Attention to energy conservation emerges first, peaking on October 6, 2022, with a distribution that appears approximately symmetric around this date, suggestive of a coordinated communication effort. Subsequent spikes in June 2023, December 2023, and December 2024 align with the government's recurring seasonal media campaigns aimed at promoting energy-saving behaviors. In contrast, attention to the energy crisis peaks later, on December 6, 2022, which coincides with a change in communication around the energy crisis. From December 6, 2022, the government seriously started to talk about potential power failures that could directly impact households. The distribution of this attention series is notably right-skewed, indicating a more abrupt and possibly unanticipated rise in public concern.

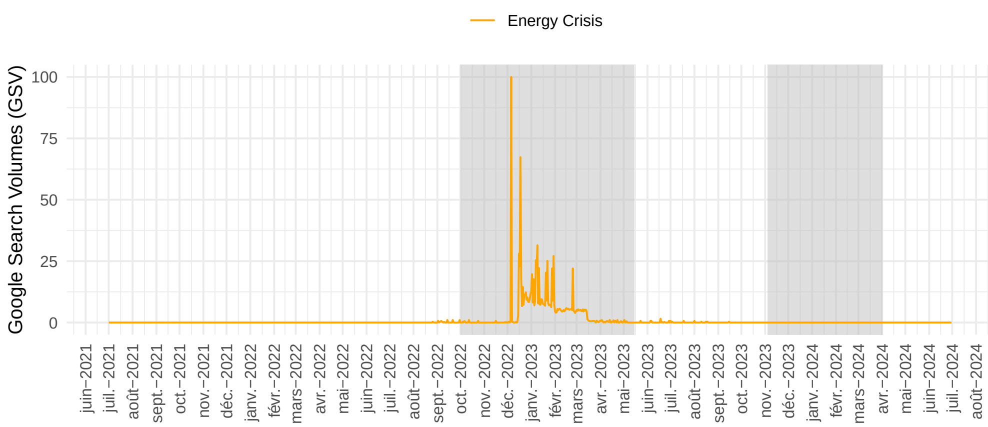
4.7 Weather Components

Given the strong thermosensitivity of residential electricity consumption in France it is essential to control for weather conditions when analysing consumption dynamics. In particular,

[10] A multi-step reconstruction algorithm is used to build a coherent daily series. Overlapping 90-day blocks are stitched together by rescaling overlaps, yielding a continuous index. The daily series is then aligned with official weekly aggregates by computing scaling factors, ensuring consistency across frequencies while preserving intra-week variation (See Figure 14 Appendix C for the scaled query).



(a) Energy Conservation



(b) Energy Crisis

Notes : The index ranges from 0 to 100, with 100 for the day with the maximum level of interest observed during the period.

Figure 5: High-frequency attention index from Google Search Volume

the significant seasonal fluctuations in consumption are largely driven by outdoor temperatures, with consumption typically around 20% higher during the winter months compared to the summer months (Bruguet et al., 2025).

To capture the main meteorological drivers of electricity demand, three daily weather indicators are constructed, in line with previous literature on the link between weather and energy consumption (Dell et al., 2014; Staffell et al., 2023; Bruguet et al., 2025). First, the outside temperature [**temp**] is measured as the 2-meter temperature above the surface (in degrees Celsius). Second, sunlight [**sunlight**] is measured as the direct solar radiation reaching the Earth's surface (in joules per square metre). Third, wind speed [**wind**] is measured as the eastward component of wind at a height of ten metres above the ground (in metres per second). Temperature is the dominant factor in explaining electricity demand fluctuations in France, due to the high prevalence of electric heating, which covers approximately 32% of the housing stock (Bouton, 2024). This relationship between temperature and energy use is highly asymmetric: while colder weather strongly increases consumption, warmer summer temperatures do not substantially reduce it (Henley and Peirson, 1997). As a result, following standard practice, *Heating Degree Days* (HDD) are constructed rather than using raw temperatures. The HDD at a given day t are defined based on a reference Base temperature of 15°C, the official threshold used for France.[11] Formally, HDD are calculated according to:

$$HDD_t = \begin{cases} 15 - T_t & \text{if } T_t < 15 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Thus, HDD capture the number of degrees below the heating threshold, reflecting the likely heating demand. Cooling Degree Days are not considered in this study, as there is no evidence of significant cooling behaviours at the national level for the residential sector in France (Bruguet et al., 2025), see Allcott and Rogers (2014) for an estimation of a cooling effect. Spatial aggregation of weather data is performed using a population-weighted approach, consistent with best practices in the literature (see for example Kennard et al., 2022). Each weather observation from the spatial grid is weighted by the associated population, using the most recent census data available, according to:

$$weather_s(pop) = \frac{weather_s \times pop_s}{\sum_{i=1}^{s} pop_i} \tag{4}$$

where $weather_s$ is the meteorological variable for cell s, pop_s is the population in that cell, and $\sum_{i=1}^{s} pop_i$ is the total population over all cells. This method ensures that national-level weather indicators reflect the conditions experienced by the majority of the population, thereby better capturing the effective drivers of aggregate residential electricity consumption.

An important pre-processing element to consider is that the daily electricity consumption data used in this study are seasonally pre-adjusted, notably for standard seasonal patterns such as weekly and holiday effects. However, they are not corrected for daily weather anomalies relative to historical norms. To isolate the effect of unusual temperature conditions, the daily HDD series is therefore centred on its historical average. This approach allows for measuring deviations in heating needs for a given day, relative to normal conditions. In Appendix C Figure 15 showcases, among other variables, the two pre-adjusted temperature and electricity consumption time-series.

[11] The choice of 15°C as the Base temperature for Heating Degree Days (HDD) in France is aligned with the national standards used by energy authorities and network operators. It reflects the temperature below which households typically start heating their dwellings. While some international studies use different thresholds, ranging from 15°C to 18°C depending on the country's building stock and heating practices (Staffell et al., 2023), the 15°C benchmark is considered appropriate for the French residential sector, given previous calibration of heating models for France (Bruguet et al., 2025).

5 Empirical Strategy

5.1 Identification Strategy

The identification strategy relies on the assumption that movements in wholesale electricity prices affect residential consumption through two distinct channels.

The first channel is institutional and operates through the regulated retail price P_e. In the French electricity market, this tariff is typically adjusted with a lag of at least six months relative to wholesale spot prices. As a result, shocks to the spot price are only gradually transmitted to the prices paid by households, which then influence electricity demand. Moreover, regulated tariffs can also be set directly by the Ministry of Energy, independently of wholesale market conditions. During the energy crisis, as described in Section 3, a tariff shield policy was implemented to limit pass-through to households. This institutional framework makes the price channel slow and, at times, partially disconnected from spot price dynamics.

The second channel is hypothesised to operate much more rapidly. Increases in wholesale prices were followed by intensive government communication campaigns emphasising both the severity of the crisis (g_{crisis}) and the need for conservation (g_{con}) and was coupled with a public service advertisement campaign (a_{con}). It is conjectured that such messages shaped public attention within weeks, fostering crisis-related awareness (m_{crisis}) and conservation-oriented attention (m_{con}). These attention variables are expected to affect electricity demand directly, even before changes in the regulated tariff occur. The empirical aim of this paper is to estimate whether this fast attention channel operated during the crisis, and to quantify its effect on consumption.

The structure of these two channels is summarised in the directed acyclic graph (DAG) presented in Figure 6. The objective is to estimate the separate causal effects of m_{crisis} and m_{con} on electricity consumption e. Identification is based on the backdoor criterion (Pearl et al., 2000), meaning that there is no need to include the communication measure if indeed the attention is derived from communication. There also exists a set of control elements X_c such as temperature, holidays and load-shedding events as they represent exogenous determinants of consumption.

5.2 Identifying Government Communication on Public Attention

This section outlines the empirical strategy used to determine the extent to which government communication and Public Interest Advertising (PSA) causally affect household attention to energy issues. The approach is grounded in a two-stage reduced-form model using narrative-specific search intensity data from Google Search Volume, where the primary interest lies in two government narratives: the energy crisis and energy conservation.

A key identification challenge arises from the high correlation between different government messages. To address this, the empirical design orthogonalizes each communication measure of interest. Let $k \in \{\text{Crisis}, \text{Conservation}, \text{Joint}\}$ denote the three mutually exclusive categories of government narratives. With *Crisis* containing only communications about the energy crisis, *Conservation* containing only communications about energy conservation, and *Joint* containing only communications with main messages about both the energy crisis and energy conservation. For each day t, the communication variable $g_{k,t}$ is projected onto

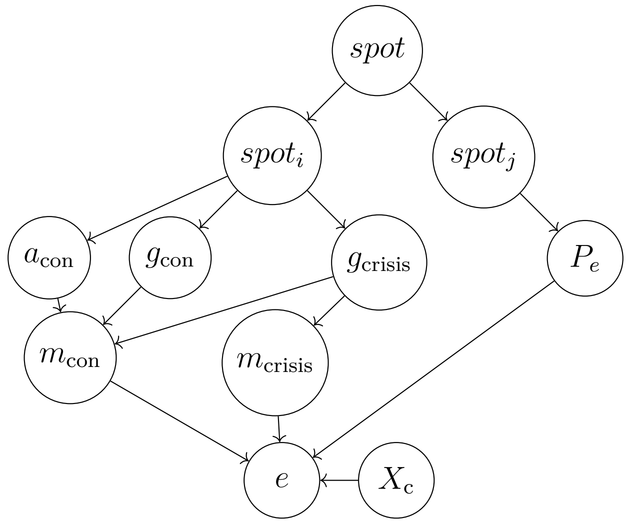


Figure 6: Directed Acyclic Graph (DAG)

the remaining two narratives, yielding residual variation $\hat{u}_{k,t}$ that is uniquely attributable to narrative k. This orthogonalized communication measure is then used as an explanatory variable, alongside the PSA variable ($a_{\text{con},t}$), in a second-stage regression predicting Google search activity for the same narrative. The general structure of the estimation is illustrated by the system below, Eq. 5, where attention to energy conservation ($m_{\text{con},t}$) is modelled.

$$\begin{aligned} g_{\text{con},t} &= \alpha_1 g_{\text{crisis},t} + \alpha_2 g_{\text{joint},t} + u_t \\ m_{\text{con},t} &= \rho\, m_{\text{con},t-1} + \delta_1 g_{\text{crisis},t} + \delta_2 g_{\text{joint},t} + \delta_3 \hat{u}_t + \delta_4 a_{\text{con},t} + \varepsilon_t \end{aligned} \tag{5}$$

The term δ_3 captures the marginal association between narrative-specific government communication and household attention, net of other correlated narratives or overall communication intensity.

To improve the credibility of the strategy, all specifications are estimated iteratively across a grid of rolling aggregation windows and communication weighting schemes. Eleven window lengths are considered, ranging from 1 to 90 days. For each window, communication variables are constructed under three different schemes: raw counts of statements, unweighted buzz scores based on keyword presence, and title-weighted buzz scores, which assign greater weight to statements with narrative keywords appearing in the title, as described in section 4.4. These variants are evaluated using the Akaike Information Criterion (AIC) and adjusted R^2 to determine the specification that best captures the relationship between communication and attention.

This procedure yields three key outputs. First, the cumulative number of days with communication before attention rise. Second, the coefficients $[\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3, \hat{\delta}_4]$ from the optimal model specification are stored for subsequent interpretation. Third, the fitted values from the second-stage regression are used to construct a measure of narrative-induced attention, denoted $m(g)_{k,t}$, which isolates the share of observed attention attributable to government communication.These series serve as the intermediate step between communication and behavior.

5.3 Electricity Estimations via an Error Correction Model

Based on Jamissen et al. (2024) and Loi and Loo (2016), the French residential consumption for electricity is modeled using an ARDL:

$$e_{i,t} = \alpha_i + \sum_{k=1}^{p} \gamma_{i,k} e_{i,t-k} + \sum_{j=1}^{n} \sum_{l_j=0}^{q_j} \beta_{j,i,l_j} x_{j,i,t-l_j} + \epsilon_{i,t}, \tag{6}$$

where $e_{i,t}$ represents the seasonally adjusted electricity consumption for tariff profile i of the residential sector at day t, without accounting for weather variability. The model incorporates a set of explanatory variables, denoted by the vector $\mathbf{x}_{j,i,t}$. Specifically, $x_{HDD,t}$ represents heating degree days (HDD), used to quantify heating needs based on outdoor temperature. $x_{solar,t}$ and $x_{wind,t}$ denote, respectively, solar radiation and wind speed, other meteorological factors influencing consumption patterns. $x_{price,i,t}$ is the varying part of the national regulated electricity tariff, without taxes, which serves as a proxy for the consumer-paid price of electricity.[12] Then, $x_{m(g)_{i,t}}$ reflects a moving average in consumer attention (m) related to government incentives (g). While changes in attention are not necessarily assumed to have direct effects on electricity use, sustained or repeated exposure to these narratives may alter consumption patterns over time (Allcott and Rogers, 2014). Accordingly, each constructed series $m(g)_{i,t}$ is subsequently smoothed over multiple potential time horizons.

Finally, the specification incorporates a binary variable, x_{dry}, which equals one during periods of load control implemented by the grid operator. This variable captures the structural reduction of discretionary demand when hot-water systems are remotely curtailed. In practice, x_{dry} enters both as a main effect and through interaction with the attention variables. The combined coefficients of each pair (e.g. conservation attention and its load control interaction) are then tested jointly, allowing the estimation of communication effects separately during and outside of load-control periods. This specification ensures that the interpretation of attention-induced demand adjustments reflects the institutional constraint of reduced flexibility in load control periods, while still capturing their potential amplifying effect in normal conditions.[13]

As control variables, but not interpreted in the results, the model also integrates a binary indicator for lockdowns during COVID-19, for holidays and for the subscription part of the pricing scheme, following Auray et al. (2019). The model residuals, $\epsilon_{i,t}$, are assumed to follow a centered normal distribution, $\epsilon_{i,t} \sim N(0, \sigma^2_{\epsilon_{i,t}})$. The lag parameters p and q are selected by minimising the Akaike Information Criterion (AIC).

Beyond this initial specification, the ARDL model, if cointegration exists, can be reframed as a Restricted Error Correction Model (RECM):

$$\Delta e_{i,t} = \underbrace{\phi_i \left(e_{i,t-1} - \sum_{j=1}^{n} \theta_{i,j} x_{j,i,t-1} \right)}_{\text{Correction towards long-term equilibrium}} + \underbrace{\sum_{k=1}^{p-1} \lambda_{i,k} \Delta e_{i,t-k}}_{\text{Inertia of demand}} + \underbrace{\sum_{j=1}^{n} \sum_{l_j=0}^{q_j} \delta_{j,i,l_j} \Delta x_{i,j,t-l_j}}_{\text{Short-term effects of } x_{j,i}} + \epsilon_{i,t}, \tag{7}$$

[12] The specification is supposed to be linear, in particular because, as emphasised by Jamissen et al. (2024), the transformation of raw temperature into HDD already embeds the nonlinearity of heating needs. The remaining relationship between HDD and energy demand is well approximated by a linear form.

[13] See Appendix D for the exact formulation of combined effects and their standard errors.

with ϕ_i defined as the speed of adjustment towards the equilibrium relationship, represented in parentheses, and also called the long-term dynamics.[14] The third term, using first-order differences of independent variables, captures the short-term dynamics.

The choice of the ARDL/RECM framework is motivated by three considerations. First, it is well established in the energy demand literature (e.g. Jamissen et al., 2024; Loi and Loo, 2016), and offers a tractable single-equation alternative to VAR or VECM models. Second, its ECM representation, that exists only if cointegration exists i.e. if $\phi_i \neq 0$, allows for a natural distinction between short-run responsiveness of electricity demand (e.g. to weather shocks or communication campaigns) and long-run equilibrium relationships, which is particularly relevant when analysing household behaviour during crisis periods. Third, it is particularly flexible with respect to the order of integration: RECM estimations remain valid when regressors are a mixture of $I(0)$ and $I(1)$ series, which is typically the case in this context (e.g. weather variables are stationary, while prices and crisis-related attention measures may be highly persistent). Moreover, the framework accommodates heterogeneous lag structures across regressors, enabling the model to capture thermal inertia in heating and behavioural frictions in price or communication responses.

To test for cointegration, the bounds testing procedure of Pesaran et al. (2001) is applied. This approach evaluates whether the adjustment coefficient ϕ_i in equation 7 is significantly different from zero. If not, no cointegrating relationship exists and the RECM form does not allow estimation of both long- and short-term effects. In this setup, unit root tests show that the price and *energy crisis* series are integrated of order one $I(1)$, whereas other series are $I(0)$ (see Appendix C, Table 12). The ARDL is therefore well suited, unlike alternative procedures that require all series to be $I(1)$ (Engle and Granger, 1987; Johansen, 1995).

The bounds test compares the test statistic to critical values for two extreme cases: all regressors $I(0)$ (lower bound) and all regressors $I(1)$ (upper bound). If the statistic exceeds the upper bound, the null of no cointegration is rejected. If it falls within the band, the result is inconclusive. Appendix C Table 13 reports the bounds tests for both Base and Off-Peak models, showing that the statistics exceed the upper bound in both cases. Hence, a cointegrating relationship is present, and the RECM form enables separation of the long-run equilibrium relation from short-run dynamics.

6 Results

This section aims to present the different results of this study. First, section 6.1 presents how government communication shapes public attention on energy savings. Then section 6.2 presents the short and long run dynamics estimates on average over the whole sample.

6.1 Government Communication as a Driver of Public Attention

The identification of government communications on public attention procedure reveals substantial differences in how the two government narratives translate into household attention.

[14] For convergence, ϕ_i must be negative, significant, and less than unity in amplitude.

First, the optimization exercise shows that the index based on the buzz metric weighted by title provides the best fit. This implies that not all government communications contribute equally to shaping public attention: messages whose key terms appear in the title, thus signaling greater salience or visibility, carry more weight in driving search behavior. Using this specification, the conservation narrative is found to elicit a very fast response, with an optimal moving average window of only two days, indicating that public attention reacts almost immediately to such messages. By contrast, the crisis narrative aligns with a much longer window of 90 days, a result largely explained by the major shift in government messaging that began on December 6, 2022. Overall, these findings suggest that information from government communication is transmitted to public attention relatively quickly, particularly when the communication is highly salient.

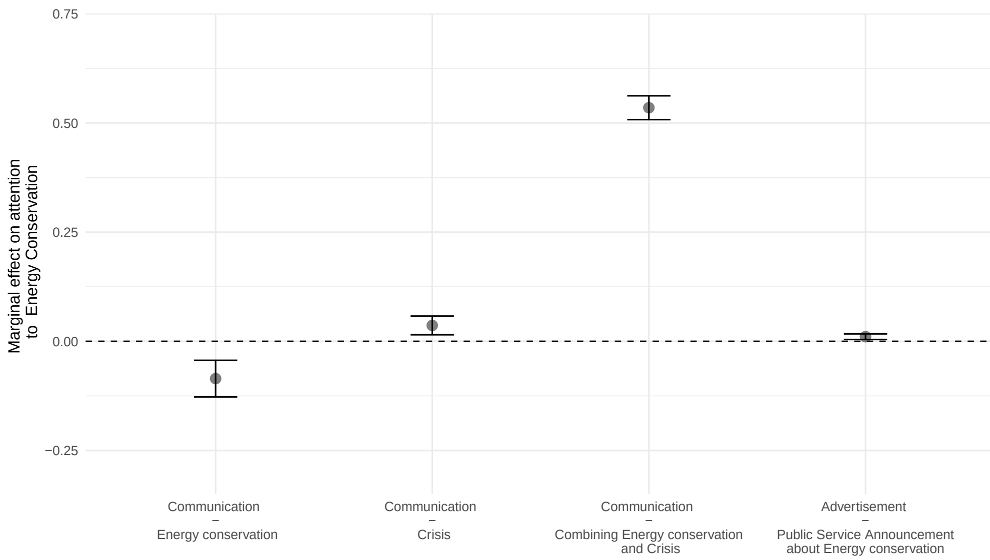
Second, the results, displayed in Figure 7, confirm that government communication meaningfully shapes public attention.[15] First, even if small, attention to the energy crisis is explained exclusively by orthogonalized government communication addressing the crisis, with no detectable effect from conservation-related messages or Public interest advertising (PSA).

In contrast, attention to energy conservation increases significantly only when conservation and crisis messages are jointly communicated, while isolated conservation appeals tend to elicit negative marginal responses. PSA on conservation generates a statistically significant but modest rise in marginal attention, of around 1%, compared to a 53% increase when the message originates from political communication embedded in a crisis frame and 3% for isolated communication about the energy crisis. This contrast highlights that households respond far more strongly when conservation appeals are delivered within a broader scarcity narrative and conveyed by a political figure, rather than through generic advertising campaigns. This asymmetry in attention aligns with evidence from behavioral economics that urgency and salience are key preconditions for the effectiveness of information-based policy instruments (see, e.g., Blasco and Gangl, 2023, Bolderdijk et al., 2013).

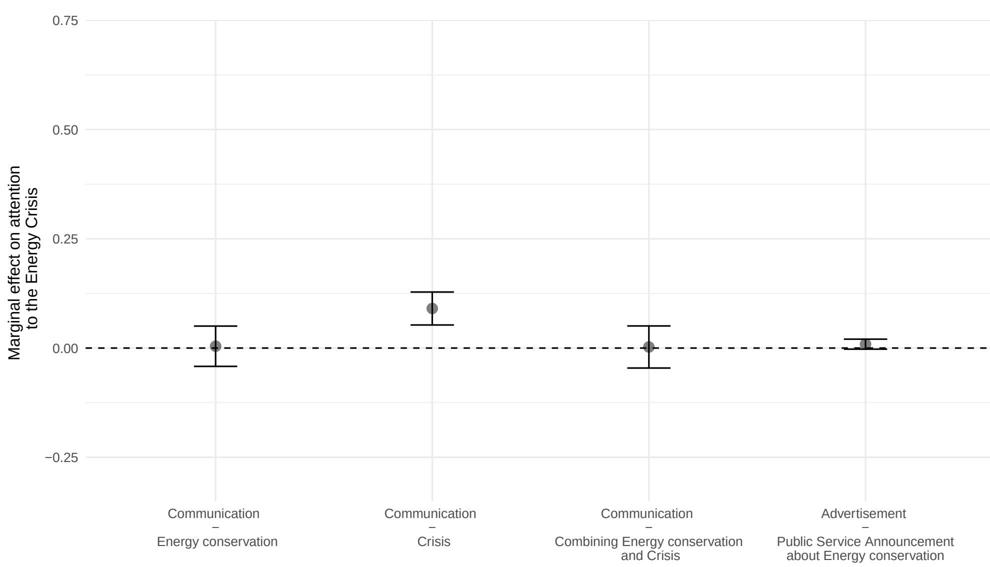
To contextualise what households were likely reacting to, a structural topic model (STM) is applied to the text of all government communication labeled as belonging to the studied narratives. The goal is to uncover the dominant content themes associated with each communication narrative (see the complete keywords lists in Appendix C, Table 9 and Table 10). For both types of narratives, the keyword "euro" emerges as highly relevant, underscoring once again the central role of fluctuations in the electricity spot market in shaping government communication. In the case of energy conservation communication, topic clusters are centered on themes such as ecological transition (keywords: "écologique," "transition," "biodiversité"), housing retrofit ("logement," "rénovation," "collectivités"), renewable energy technologies ("hydrogène," "nucléaire," "renouvelables"). These topics reflect the official tone of long-term environmental planning, public sector reform, and sustainability policy. There also exist two meaningfull cluster, first with the Russian-Ukrainian war ("armées," "européenne," "ukraine") and second one cluster about civil servants and the role of the state ("fonction public," "publique," "fonctionnaires"). The war and its consequences on the european energy system and the role of the state as an exemplar agent in energy saving efforts were two hot topic during winter 2022-2023. By contrast, energy crisis messages are

[15] The estimates are avaible in Appendix C Table 14

more often embedded in discussions of macroeconomic support (e.g., “euros,” “communes,” “collectivités,” “millions”) in particular the word "euros" appears more than thousand times highlighting the role of price narrative within this crisis communication. European coordination (“union européenne,” “Europe,” “sanctions”), and energy market volatility (“électricité,” “boulangers,” “salariés”) were also related topics.



(a) Attention to Energy Conservation



(b) Attention to Energy Crisis

Figure 7: Estimated effects of Government Communication on Public Attention

Finally, Figure 8 presents the optimal measure of public attention driven by government communication. As described, the black time series displays the attention to energy conservation within a crisis context with a peak attention during October and November 2022. The orange time series displays attention to the energy crisis. Here, the time series can take negative values since the government communicated about the crisis in October and November 2022, but the public first did not seem to pay much attention to the topic. Then, from 6 December 2022 onward, public attention reacted to government communication. A close look at the government wording around this precise date highlights that this period exactly coincides with 9 governmental statements issued between December 5 and December 13, 2022, about the increasing risk of power failure in the French electricity system.[16] It is also noteworthy that the peak in attention, both for conservation and crisis narratives, falls within the grey-shaded periods, which correspond to days when the national grid operator applied load-control measures.

In sum, the interpretation of the two attention series should be grounded in their distinct contextual meanings. First, public attention to energy conservation appears to elicit behavioral responses only when framed within the broader context of an energy crisis that puts lights on increasing prices. Second, attention to the energy crisis itself only appears once heightened concern over potential failures of the electricity supply is put forward. These interpretations guide the subsequent empirical analysis.

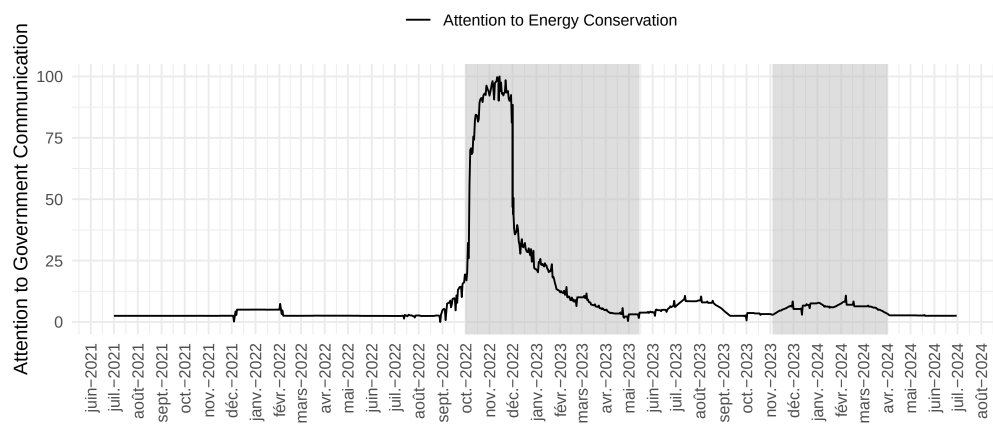
6.2 Public Attention and Energy Consumption

This section presents the estimated short-run and long-run responses of residential electricity consumption to key drivers using the ARDL-RECM framework. The analysis distinguishes between two representative household tariff profiles: Base and Peak/Off-Peak. Particular emphasis is placed on the role of attention to government communication delay into significant behavioural change. For conservation-related attention, the optimal moving average window is 60 days, suggesting that households adapt their consumption only after sustained and repeated attention, consistent with the idea of gradual adjustment through habit formation and norm internalization (Allcott and Rogers, 2014). In contrast, for crisis-related attention, the optimal window is only three days, indicating that households react almost immediately once crisis communications carry messages about potential power failures.

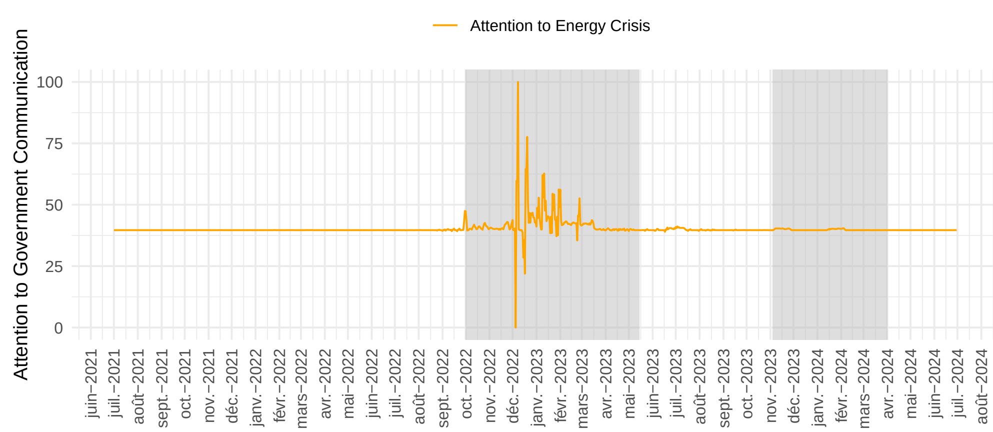
6.2.1 Short-run dynamics

The short-run dynamics differ markedly across tariff groups, as shown in Figure 9 and in Appendix C, Table 15. For households on the Base tariff, consumption responds most strongly to changes in heating degree days and electricity prices. A 1°C drop in temperature increases daily consumption by roughly 0.035 kWh per contract, while a €1/MWh increase in electricity prices reduces consumption by about 0.003 kWh per contract. These effects dissipate within two days, indicating limited inertia in short-term behaviour. No statistically significant response is detected for either energy crisis communication or energy conservation messaging in this group, suggesting that such narratives do not alter consumption in the absence of time-sensitive incentives or structural flexibility.

[16]See for exemple an interview on television of the Minister for Ecological Transition about the risks of power faillure and the need to be prepared, to have batteries and generators available.



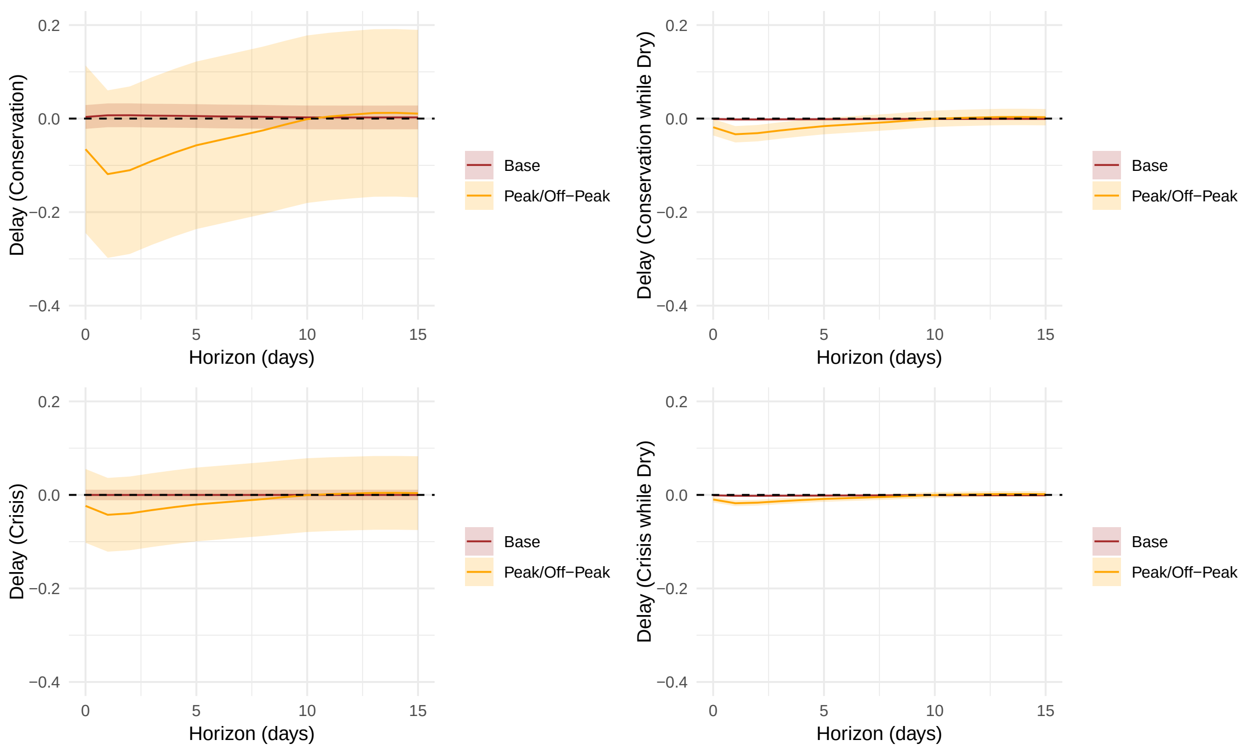
(a) Attention to Energy Conservation (MA 60 days)



(b) Attention to Energy Crisis (MA 3 days)

Figure 8: Public Attention filtered on Government Communication

By contrast, households on the Peak/Off-Peak tariff display a broader sensitivity to both market and informational shocks. Outside grid-operator control periods, communication-induced attention is associated with a sharp but statistically insignificant decline in consumption, consistent with the relatively low level of aggregate public attention during these weeks. Nevertheless, the estimated magnitudes reach up to 0.06 kWh and 0.02 kWh per contract following one-point increases in conservation and crisis related attention indices, respectively. Because these indices range from 0 to 100, a one-point increase corresponds approximately to a 1% rise in public attention to the corresponding narrative. It is important to recall, however, that conservation-related attention only emerges when accompanied by crisis communication; as shown earlier, standalone conservation messaging tends to elicit little or even declining attention to the topic. The shape of the impulse-response function indicates a delayed behavioral adjustment: consumption begins to decline one day after an increase in attention and remains lower on the second day. This pattern suggests that, when households retain full control over their electric heating and water systems, conservation messaging can prompt short-run behavioral changes with a modest lag rather than an immediate mechanical response. During load-control periods, which coincide with peaks in both crisis and conservation attention, the estimated effects become statistically significant but smaller in size, around 0.02 kWh and 0.01 kWh per contract for conservation and crisis related attention shocks, respectively. This attenuation likely reflects a reduction in available flexibility caused by remote curtailment, which limits households' ability to voluntarily adjust consumption. It is also consistent with a compositional mechanism: the households subject to remote control are precisely those that would otherwise exhibit the greatest behavioral responsiveness. Appendix A presents a robustness exercise where the load control hours have been systematically removed from daily consumption to assess communication induced attention effect without interaction.



Notes : The delay represents, on each day following the initial shock, the short-run impact in kWh/contract. Once the delay returns to equilibrium, it indicates that the shock has been fully absorbed by the system. The solid line represents the estimated coefficients and the shaded area represents the interval confidence at 95%.

Figure 9: Short-Run dynamic estimates

6.2.2 Long-run dynamics

Table 4 reports the long-run parameter estimates from the RECM specification, estimated separately for Base and Off-Peak tariff profiles. In the ARDL-RECM framework, which models electricity consumption at daily frequency, long-run coefficients capture the steady-state effects of explanatory variables after short-run fluctuations have fully dissipated. These coefficients reflect the equilibrium relationship toward which electricity demand converges in response to persistent shifts in climate, pricing, or information environments. Finally, the estimates reflect aggregate averages across a heterogeneous set of households differing in building characteristics, heating technologies, and socio-economic profiles. The estimates therefore capture population-level tendencies rather than micro-level behavioral responses.

Among households on the Off-Peak tariff, the primary drivers, temperature and electricity prices, exert statistically significant and economically meaningful long-run effects. A 1°C decrease in outdoor temperature during the heating season leads to a 0.21% increase in consumption, confirming a strong degree of thermosensitivity. This is consistent with the role of electricity in space heating in France, where roughly one-third of dwellings rely on electric heating systems (Bouton, 2024). A 1% increase in the regulated electricity tariff reduces long-run consumption by approximately 0.24%, reflecting a price elasticity broadly consistent with the findings of Loi and Loo (2016). While this elasticity is below the range reported in earlier French studies (e.g., Auray et al., 2019), it aligns with estimates obtained in similar dynamic frameworks and suggests moderate but persistent price responsiveness among residential users.

Government communication coincided with measurable long-run reductions in electricity use among Peak/Off-Peak households, but only when such messaging overlapped with the load control period, during which the national distributor remotely curtailed midday hot-water heating for roughly four million households in this tariff group. During this interval of simultaneous mechanical load reduction and intensified public appeals for energy savings, a 100% increase in public attention to crisis related messaging, particularly narratives emphasising potential supply shortfalls, is associated with a statistically significant 0.30% decline in equilibrium consumption. Yet, the largest estimated reduction arises from conservation related attention. A comparable 100% rise in attention to conservation narratives, conditional on concurrent crisis communication, corresponds to an estimated 0.50% decrease in equilibrium consumption. Although this effect is less precisely estimated and narrowly misses conventional significance thresholds, its magnitude suggests that conservation oriented communication, when embedded within a salient crisis context, may exert a stronger behavioural influence than crisis attention alone. The weaker precision likely reflects a diminished reservoir of discretionary load, as a substantial share of flexible capacity was already under compulsory curtailment during the control period. The magnitude of these effects aligns with evidence from Germany, where Jamissen et al. (2024) documents a decrease of 0.90% for household gas usage when search intensity for the keyword *"Energiekrise"* in Google increases by 100%. Together, the findings suggest that when credible government communication coincides with visible system stress and complementary operational interventions, it can reinforce and extend consumption reductions beyond the short run.

By contrast, long-run adjustments among Base tariff households are more limited. The only statistically and economically significant determinant of equilibrium consumption is electricity price. A 1% increase in regulated tariffs leads to a 0.17% decrease in consumption. No significant effect is detected for temperature or public attention, suggesting that consumption among Base tariff users is less flexible and less sensitive to informational or climatic variation.

For a representative household under the Off-Peak tariff, Figure 10 presents the long-run

Table 4: Long-Run estimates

	Base Profile					Off-Peak Profile				
	Elasticity	Estimate	Std. Error	t-value	Pr(>|t|)	Elasticity	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)		**4.5638*****	0.8567	5.3270	0.0000		**14.2250*****	1.5297	9.2990	0.0000
x_{pt}	**-0.1694%*****	-0.0114***	0.0027	-4.2239	0.0000	**-0.2111%*****	-0.0329***	0.0048	-6.8349	0.0000
x_{HDD}	0.0125%	0.0236	0.0535	0.4406	0.6595	**0.2395%*****	1.0072***	0.0661	15.2407	0.0000
$x_{m(g)_{con}}$	0.0047%	0.1367	0.6134	0.2229	0.8237	-0.0092%	-0.5924	0.9871	-0.6001	0.5485
$x_{m(g)_{crisis}}$	-0.0001%	-0.0025	0.2700	-0.0092	0.9926	-0.0037%	-0.2120	0.4342	-0.4882	0.6254
x_{dry}	0.0018%	0.0671	0.1597	0.4200	0.6740	**-0.0097%*****	–0.7970***	0.2553	-3.1215	0.0018
$x_{m(g)_{con}\|dry}$	-0.0053%	-0.1729	0.6211	-0.2784	0.7807	0.0059%	0.4251	0.9991	0.4255	0.6705
$x_{m(g)_{crisis}\|dry}$	-0.0013%	-0.0340	0.2713	-0.1255	0.9001	0.0020%	0.1232	0.4356	0.2829	0.7773
$x_{m(g)_{con}+dry}$	-0.0024%	-0.0362	0.0594	-0.6094	0.5423	**-0.0049%***	–0.1673*	0.0958	-1.7467	0.0807
$x_{m(g)_{crisis}+dry}$	-0.0028%	-0.0365	0.0229	-1.5983	0.1100	**-0.0030%*****	–0.0888***	0.0350	-2.5359	0.0112
R^2		0.9898					0.9826			
N		1839					1839			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes : Estimates are expressed in kWh/day/contract, with data from 01/07/2019 to 30/06/2024.

estimates in a more explicit manner. Average annual consumption fell by 0.9 MWh between 2019–2021 and 2022–2023. Of this decrease, 0.47 MWh can be attributed to increases in electricity prices, 0.15 MWh to milder winter temperatures, 0.15 MWh to power cuts operated by the public distributor, and respectively 0.08 MWh (around 9%) and 0.05 MWh (around 5%) to Conservation-related and Crisis-related attention induced by government communications. These effects demonstrate the value of coordinated price signals and crisis-framed informational campaigns as complementary tools for managing residential energy demand in constrained settings.

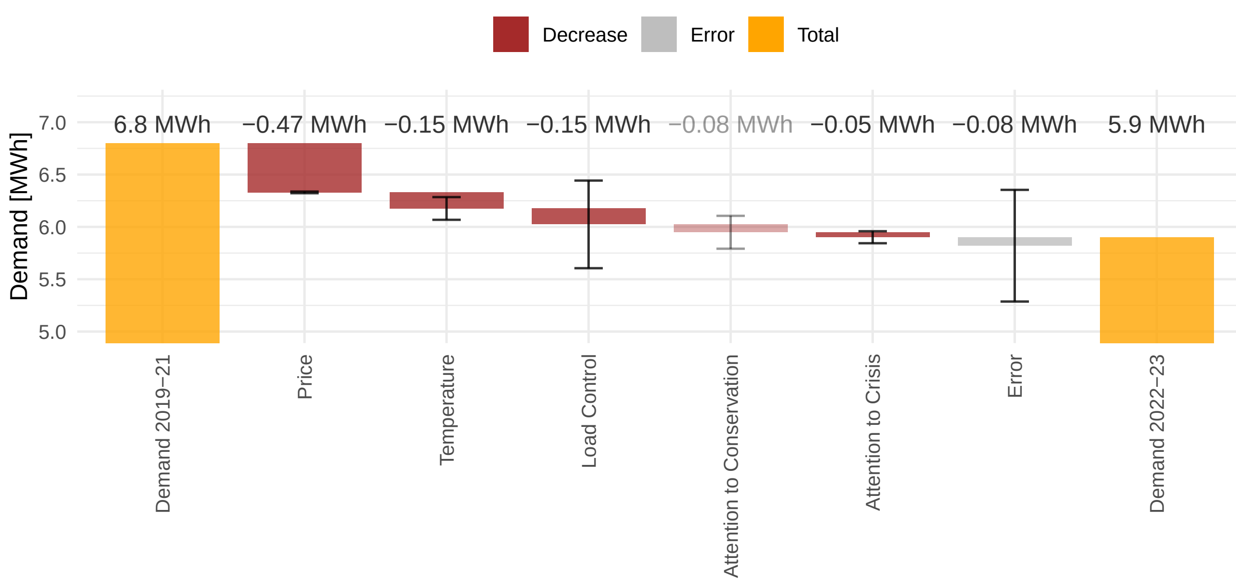


Figure 10: Electricity Decrease Decomposition (Peak/Off-Peak)

7 Policy Implications

The findings underscore that informational campaigns can reduce household electricity demand, but their effectiveness depends critically on context, household characteristics, and institutional constraints. Three main implications follow.

Attention to energy conservation emerged only when communication was framed in terms of crisis and scarcity. Generic appeals even carried a decreasing marginal attention for the topic. This suggests that informational campaigns are most effective when deployed as behavioural amplifiers during periods of systemic stress, such as anticipated shortages or disruptions, rather than as stand-alone instruments in normal times. Communication strategies should therefore be carefully timed and framed to maximise salience and credibility. This pattern is consistent with a literature documenting that consumer attention is scarce, costly, and decays rapidly over time (e.g. Allcott and Kessler, 2019; List et al., 2023). This result highlights the hypothesis that households face not only a budget constraint but also a cognitive constraint: they cannot attend equally to all dimensions of decision-making, and energy use competes with other priorities for their limited attention.

Only price-flexible households, those on Peak/Off-Peak tariffs, translated attention into significant reductions in electricity consumption. Base-tariff households, which structurally consume less and have fewer electric end-uses, showed little sensitivity to informational appeals. Policies should therefore be differentiated: informational campaigns may be best targeted at flexible users already exposed to dynamic pricing or energy-saving technologies, while less responsive groups may require transfers, or structural efficiency investments.

The scope for voluntary reductions was partly constrained by operator-led load control, such as the curtailment of midday water heating during the crisis. These interventions mechanically reduced the pool of flexible demand and may have muted the impact of conservation-related attention. This highlights a potential trade-off: centrally imposed load control ensures immediate system stability but can reduce the room for behavioral responses. Policy design should therefore consider how operator actions and household-level flexibility interact, ensuring that demand-side engagement is not crowded out.

Taken together, the evidence indicates that government communication can enhance demand-side flexibility during crises, but its effectiveness is conditional: it works best when scarcity is salient, when households are structurally able to adjust, and when institutional measures do not preempt voluntary responses.

8 Conclusion

This paper asked whether government communication can shape household electricity demand during a crisis. To address this question, it combined more than 12,000 official statements with narrative-specific attention indices and tariff-disaggregated daily consumption data. By tracing the sequence from communication to attention and from attention to demand, the design isolates the behavioural channel through which public appeals translate into consumption responses.

The results show that conservation-oriented attention arose only when messaging was framed within a broader crisis narrative, whereas crisis-related communication drew immediate attention on its own, particularly during periods of heightened reliability concerns. Attention for energy related topics explained up to 14% of the reduction in demand, though its impact was partially muted by operator-led load control curtailed discretionary flexibility. By contrast, prices and temperatures exerted the largest and most persistent effects, with especially strong responses among households on Peak/Off-Peak tariffs. Together, these findings demonstrate that communication can mobilise attention and contribute to demand reductions, but only under conditions where scarcity is salient and households retain room to adjust.

The policy implication is that communication should be viewed not as a stand-alone instrument but as a complement to prices and institutional measures. It is most effective when framed around credible scarcity risks, targeted toward households with structural flexibility, and coordinated with system-level interventions to avoid crowding out voluntary responses. Outside such contexts, its capacity to deliver sustained reductions in household electricity use appears limited.

This underscores more broadly both the potential and the limits of communication as a demand-side policy tool: powerful when urgency is high, but unlikely to sustain adjustments once crisis conditions abate.

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A Robustness Without Load Control Hours

The daily consumption between 11:00 a.m. and 4:00 p.m. was set to zero to remove the direct influence of the load-control intervention, during which the grid operator remotely curtailed hot-water heating. This adjustment isolates voluntary behavioral responses by ensuring that estimated effects are not mechanically driven by enforced curtailment. A limitation is that any behavioral adaptation occurring precisely during these hours will no longer be captured.

Table 5 and Figure 11 provide a descriptive comparison of electricity demand with and without these hours. Total residential consumption during the 2022–2023 winter remains almost identical to the baseline, with an overall reduction of about 8% relative to pre-crisis years, slightly smaller than the 8.6% observed when midday hours are included. The difference is concentrated among Peak/Off-Peak households, whose consumption falls by 12.5% once load-control periods are removed, compared with 13% in the full sample. Base-tariff households show a modest decline of –3%, unchanged across specifications. Figure 11 further illustrates that trimming the midday interval eliminates the sharp dip between 11:00 and 14:00 visible in the main hourly profiles, while leaving morning and evening peaks unaffected. The resulting load curve is smoother and more representative of voluntary rather than operator-induced adjustments.

Figure 12 and 13 showcase the short and long run estimates. Re-estimating the models on this adjusted dataset leaves the main physical and economic drivers of electricity demand essentially unchanged. For Base-tariff households, temperature and price effects remain robust, while attention-related variables continue to show no significant influence on consumption, confirming the absence of behavioral flexibility among this group. In contrast, for Peak/Off-Peak households, attention retains a clear and significant role in shaping electricity use even after the exclusion of load-controlled hours. In the short run, increases in both conservation- and crisis-related attention continue to reduce electricity consumption, with estimated effects of roughly –0.025 kWh and –0.009 kWh per contract following a one-point rise in the corresponding attention indices. In the long run, these negative relationships persist, with elasticities of around –0.004% for conservation and –0.002% for crisis attention, alongside the expected strong sensitivity to both temperature and prices.

These results confirm that the direction, timing, and statistical significance of the communication, attention, consumption link remain stable once the mechanically constrained hours are removed. The slight attenuation in magnitude relative to the main specification reflects the trimming of periods when communication intensity and system stress most often coincided. Overall, the robustness exercise reinforces the interpretation that communication induced attention operates primarily through discretionary flexibility: it continues to reduce electricity use when households retain the ability to adjust their behavior freely.

Table 5: Average Annual Electricity Consumption - Without Load Control Hours

Panel A. Total electricity consumption (TWh)				
	2019–2021	2022–2023	Difference	%
Base	37.2	36.5	-0.7	-1.8
Peak/Off-Peak	75.0	65.6	-9.3	-12.5
Total	94.1	86.3	-7.8	-8.3
Panel B. Average consumption per contract (MWh/contract)				
	2019–2021	2022–2023	Difference	%
Base	2.1	2.0	-0.1	-3.3
Peak/Off-Peak	5.2	4.6	-0.6	-12.2
Total	6.1	5.5	-0.6	-9.9

Notes : Years are defined from July to July in order to encompass one winter period per year of study. Thus, the year 2022 goes from July 2022 to June 2023.

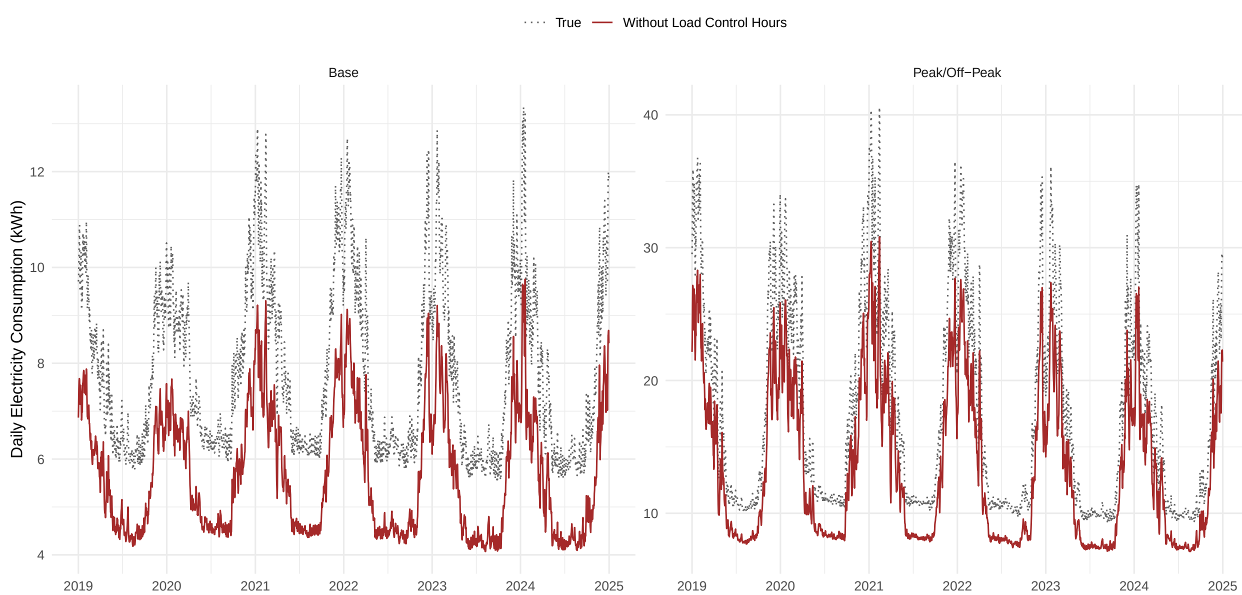
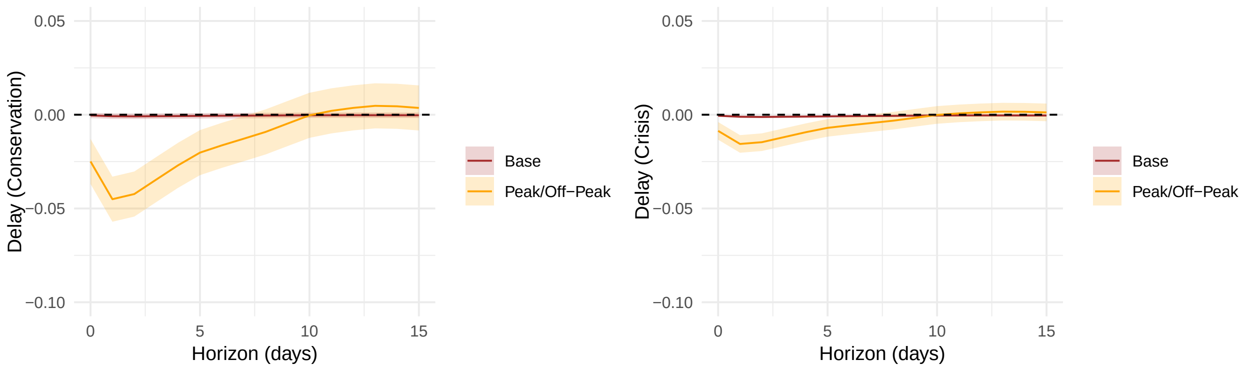


Figure 11: Daily Electricity Consumption with and without Load Control Hours



Notes : The delay represents, on each day following the initial shock, the short-run impact in kWh/contract. Once the delay returns to equilibrium, it indicates that the shock has been fully absorbed by the system. The solid line represents the estimated coefficients and the shaded area represents the interval confidence at 95%.

Figure 12: Short-Run dynamic estimates - Without Load Control Hours

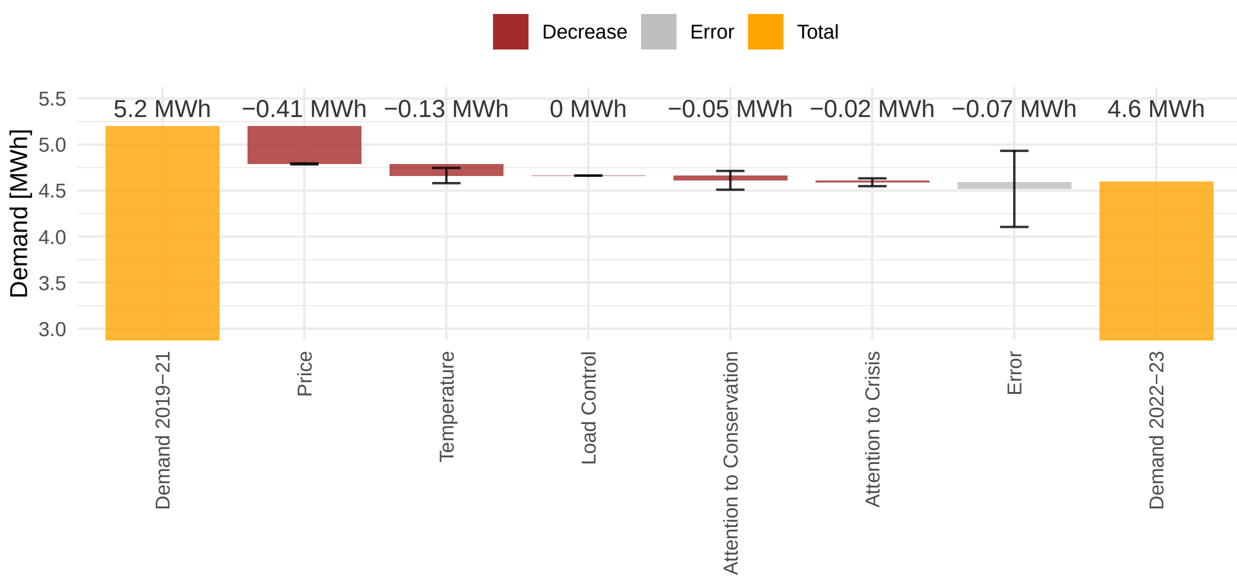


Figure 13: Electricity Decrease Decomposition (Peak/Off-Peak) - Without Load Control Hours

B Complementary Background

Table 6: Summary of Data Sources and Coverage

Source	**Frequency**	**Coverage**	**Notes**
Enedis Open Data	Daily	01/2019-04/2024	95% of mainland households
ECMWF	Daily	01/2019-04/2024	Population-weighted averages
CRE	Bi-annual	01/2019-04/2024	Weighted by contract distribution
ENTSO-E	Daily	01/2019-04/2024	European Transparency Platform
Vie Publique	Daily	01/2019-04/2024	Classified into crisis and conservation narratives
Google Trends	Daily	01/2019-04/2024	Scaled 0–100; proxy for public attention

Notes : All variables are aggregated to daily frequency for consistency. Weather indicators are weighted by population across regions. Retail tariffs correspond to regulated price schedules, while wholesale prices represent day-ahead market quotations. Public communication data are manually classified by narrative using a semi-supervised algorithm.

Table 7: Yearly rate change in the number of contracts by profile (%)

periode	Base	Peak/Off-Peak	Tempo	Total
2019-01-01				
2020-01-01	+1.65 %	+0.96 %	-5.17 %	+1.28%
2021-01-01	+2.03 %	-0.56 %	-6.53 %	+0.80%
2022-01-01	+2.28 %	-0.40 %	+0.66 %	+1.07%
2023-01-01	-0.60 %	+1.43 %	+92.05 %	+0.89%
2024-01-01	-0.63 %	+0.23 %	+100.91 %	+0.98%

Notes : Between 2020-01-01 and 2021-01-01, the basecontracts increased by 2.0%, Peak/Off-Peak decreased by 0.6 % and Tempo decreased by 6.5%. Overall, Enedis acquired around 1% new contracts every year between 2019 and 2024.

Table 8: CRE suggested tariffs without tariff shield

Resolution	Date	TRV (CRE)	TRV (Government)
2022-08	janv-22	+20.0%	+4.0%
2022-198	juil-22	+3.9%	+4.0%
2023-17	janv-23	+72.9%	+15.0%
2023-148	juin-23	+0.9%	+37.1%

Notes : The CRE's variations in tariffs are indeed those considered in the case where there is never a tariff shield applied from one period to the next, but does take into account the reduction in the TICFE.

C Complementary Results

C.1 Tables

Table 9: Topics within Government Communication about Energy Conservation

Cluster	Keyword	Count
Cluster_3 (40)	écologique	331
	transition	351
	transition écologique	222
	biodiversité	153
	euros	311
Cluster_9 (23)	électricité	271
	nucléaire	212
	prix	264
	énergies	148
	renouvelables	110
Cluster_7 (21)	armées	159
	européenne	283
	ukraine	168
	europe	221
	défense	138
Cluster_2 (18)	logement	397
	logements	302
	rénovation	350
	collectivités	174
	bailleurs	80
Cluster_5 (15)	fonction publique	341
	publique	387
	fonction	377
	agents	198
	fonctionnaires	78
Cluster_0 (12)	gaz	167
	électricité	99
	hiver	54
	prix	74
	consommation	48
Cluster_1 (12)	hydrogène	290
	nucléaire	216
	production	218
	énergies	209
	renouvelables	155
Cluster_4 (7)	sport	420
	jeux	251
	sportive	142
	olympiques	134
	sportifs	126
Cluster_8 (5)	élèves	100
	école	94
	enseignants	94
	rentrée	56
	scolaire	56
Cluster_6 (3)	extrême	9
	extrême droite	6
	assemblée	20
	compatriotes	8
	débat	17

Table 10: Topics within Government Communication about Energy Crisis

Cluster	Keyword	Count
Cluster_0 (38)	euros	1005
	collectivités	730
	communes	432
	millions	599
	milliards	570
Cluster_1 (35)	européenne	652
	union	437
	union européenne	357
	européen	353
	europe	321
Cluster_7 (29)	emploi	355
	chômage	195
	réforme	160
	euros	213
	pouvoir	223
Cluster_3 (23)	industrie	171
	délégué	233
	production	199
	euros	233
	plan	220
Cluster_5 (10)	électricité	61
	etat	41
	matin	48
	boulangers	21
	salariés	37
Cluster_6 (9)	russie	145
	ukraine	128
	guerre	92
	sanctions	55
	europe	74
Cluster_2 (8)	députés	58
	majorité	57
	eau	60
	assemblée	67
	pouvoir	79
Cluster_9 (7)	finances	63
	publiques	62
	euros	79
	milliards	83
	croissance	54
Cluster_8 (6)	industrie	108
	véhicules	27
	etats unis	26
	etats	29
	production	42
Cluster_4 (4)	application	105
	pouvoir	82
	sénat	66
	présidente parole	40
	législatif	50

.

Table 11: Top Search Queries related to Energy Conservation and Energy Crisis

Panel A. Energy Conservation	
French	English
sobriété énergétique	energy conservation
plan de sobriété	conservation plan
la sobriété énergétique	energy conservation
la sobriété	conservation
définition sobriété	definition of conservation
sobriété énergétique gouvernement	government energy conservation
sobriété énergétique définition	definition of energy conservation
plan sobriété énergétique	energy conservation plan
plan de sobriété énergétique	energy conservation plan
Panel B. Energy Crisis	
French	English
crise énergétique	energy crisis
crise énergétique européenne france	European and French energy crisis
crise énergétique européenne	European energy crisis
crise énergétique europe	energy crisis in Europe
crise énergétique 2022	2022 energy crisis
la crise énergétique en france	energy crisis in France
la crise énergétique	the energy crisis
crise énergétique pourquoi	why the energy crisis
crise énergétique france	France energy crisis

Table 12: Unit-Roots Tests

	Level - $I(0)$				First Difference -$I(1)$			
	ADF		PP	KPSS	ADF		PP	KPSS
	Lags	*Statistics*	*P-value*	*P-value*	*Lags*	*Statistics*	*P-value*	*P-value*
e_t	9	-7.97***	0.01	0.01	8	-16.69***	0.01	0.1
x_{HDD}	4	-12.22***	0.01	0.10	5	-22.94***	0.01	0.1
x_{price}	1	-0.44	0.49	0.01	1	-30.33***	0.01	0.1
$x_{m(g)_{con}}$	8	-3.51	0.48	0.02	10	-10.50***	0.01	0.1
$x_{m(g)_{crisis}}$	10	-5.34***	0.01	0.01	10	-26.09***	0.01	0.1
x_{dry}	1	-2.45	0.24	0.01	1	-30.27***	0.01	0.1

Notes : The lag column represents the number of lags included in the ADF regression, guided by the Akaike Information Criteria.

Table 13: Co-integration bounds tests

	F-statistics	Statistic	Lower-bound $I(0)$	Upper-bound $I(1)$
Base model	6.02	-5.43***	-3.43	-4.98
Off-peak model	22.73	-12.29***	-3.43	-4.98

Notes : Critical bounds are provided at 1% significance level

Table 14: Estimation of orthogonalised attention to communication

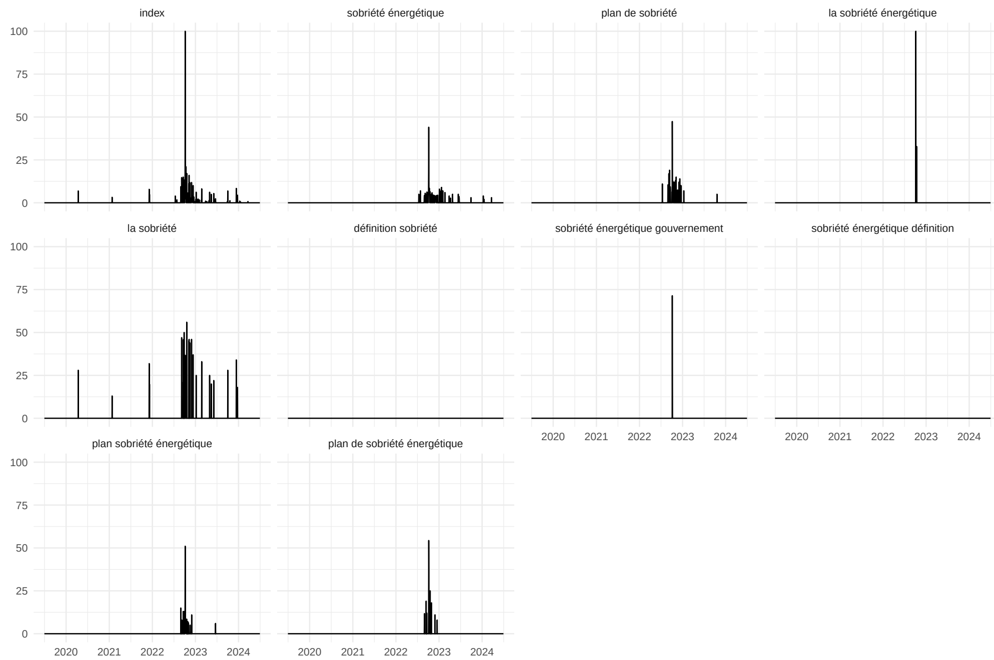
	Dependent variable:	
	Attention m_i	
	Conservation	Crisis
lag(m_i)	0.481***	0.411***
	(0.025)	(0.022)
$\hat{u}_{con}$	−0.085***	
	(0.021)	
$\hat{u}_{crisis}$		0.091***
		(0.019)
g_{joint}	0.535***	0.002
	(0.014)	(0.025)
g_{crisis}	0.036***	
	(0.011)	
g_{con}		0.004
		(0.024)
a_{con}	0.011***	0.009
	(0.003)	(0.006)
Observations	1,738	1,738
R^2	0.718	0.689
Adjusted R^2	0.717	0.688
Residual Std. Error (df = 1733)	1.993	3.588
F Statistic (df = 5; 1733)	881.960***	767.137***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 15: Short-Run estimates

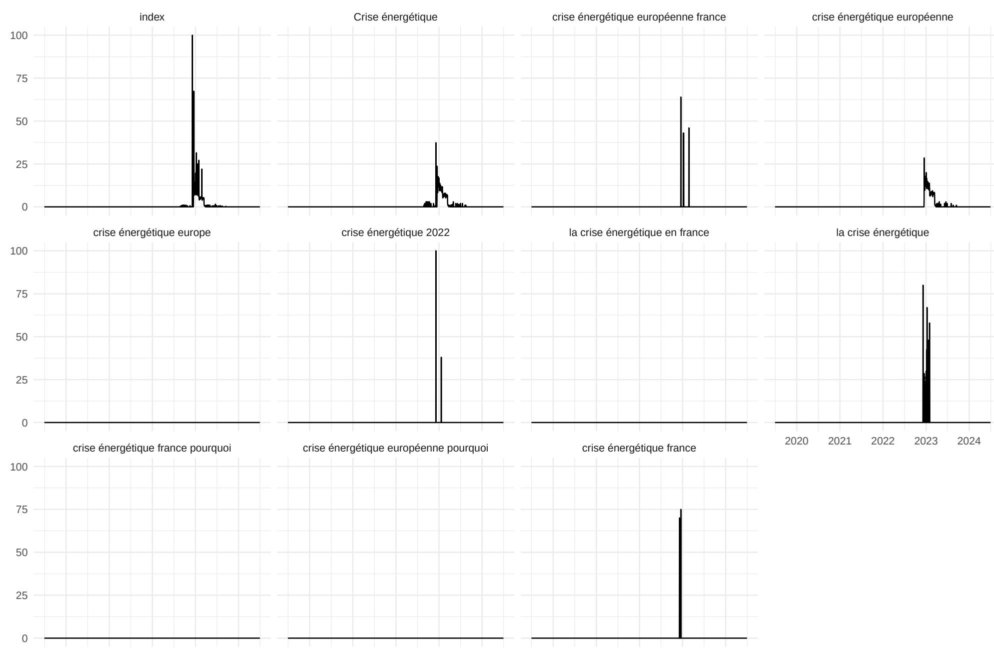
	Base Profile (Short-run)					**Off-Peak Profile (Short-run)**				
	Elasticity	Estimate	Std. Error	t-value	Pr(>|t|)	Elasticity	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)		**0.1154***	0.0325	3.5530	0.0004		**1.5736***	0.2243	7.0165	0.0000
x_{pt}	**-0.0438%***	–0.0029***	0.0010	-2.8843	0.0040	**–0.1503%***	–0.0233***	0.0086	-2.7213	0.0066
x_{HDD}	**0.0186%***	0.0351***	0.0013	26.740	0.0000	**0.0848%***	0.3567***	0.0086	41.342	0.0000
$x_{m(g)_{con}}$	0.0001%	0.0035	0.0155	0.2229	0.8236	-0.001%	-0.0655	0.1092	-0.6000	0.5486
$x_{m(g)_{crisis}}$	0.0000%	-0.0001	0.0068	-0.0092	0.9926	-0.0004%	-0.0235	0.0481	-0.4877	0.6259
x_{dry}	0.0000%	0.0017	0.0041	0.4179	0.6760	**–0.0011%***	–0.0882***	0.0297	-2.9691	0.0030
$x_{m(g)_{con}\|dry}$	-0.0001%	-0.0044	0.0157	-0.2784	0.7807	0.0007%	0.0470	0.1105	0.4255	0.6705
$x_{m(g)_{crisis}\|dry}$	0.0000%	-0.0009	0.0069	-0.1257	0.9000	0.0002%	0.0136	0.0482	0.2827	0.7774
$x_{m(g)_{con}+dry}$	-0.0001%	-0.0009	0.0015	-0.6045	0.5455	**-0.0005%***	-0.0185*	0.0107	-1.7306	0.0835
$x_{m(g)_{crisis}+dry}$	-0.0001%	-0.0009	0.0005	-1.7038	0.0884	**-0.0003%***	-0.0098*	0.0038	-2.5827	0.0098
R^2		0.9898					0.9826			
N		1839					1839			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes : Estimates are expressed in kWh/day/contract, with data from 01/07/2019 to 30/06/2024.

C.2 Figures



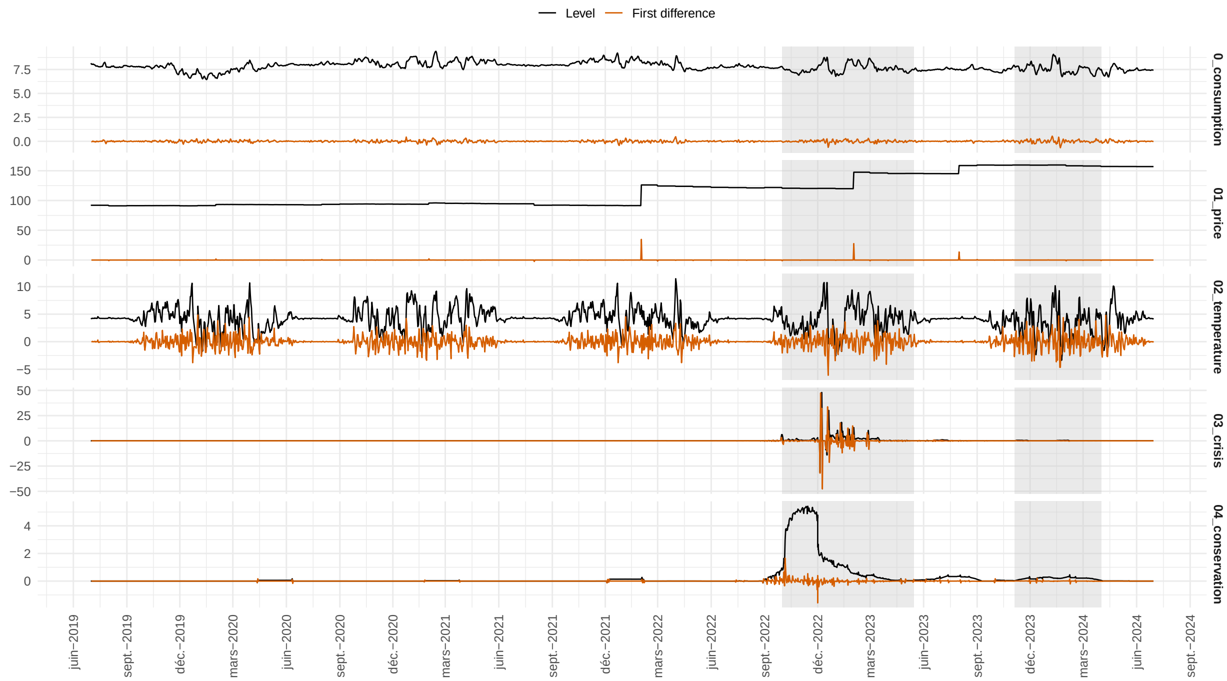
(a) Energy Conservation



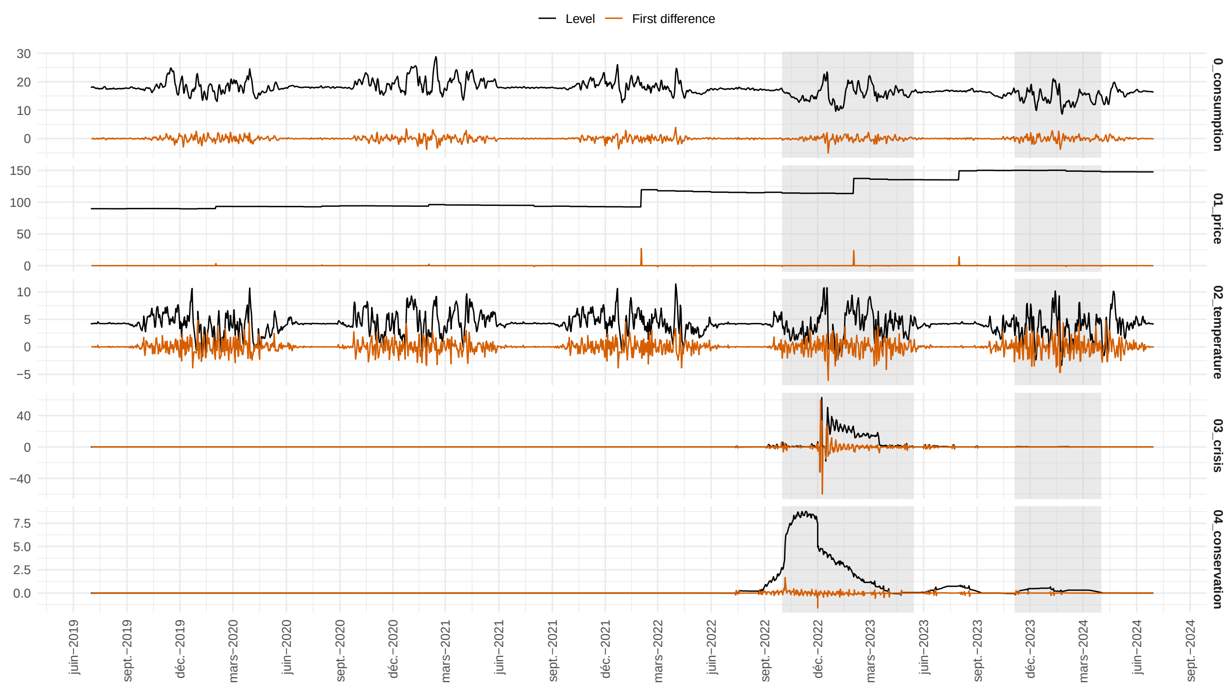
(b) Energy Crisis

Notes : Index represents the normalised to 100 mean of the different queries. Some queries are not different from 0 over the period because they had only periodic importance that erases after harmonisation with weekly frequency search.

Figure 14: Top Related Query after Normalisation by Weekly Frequency



(a) Base



(b) Peak/Off-Peak

Figure 15: Level and First Difference Main Regressors

D Computation of Combined Effects During Load-Control Periods

When an attention variable x_m enters both directly and through interaction with the load-control dummy x_{dry}, the specification reads as in Eq 8.

$$e_t = \ldots + \beta_m x_{m,t} + \beta_{m\times dry}\,(x_{m,t} \times x_{dry,t}) + \epsilon_t. \tag{8}$$

The short-run effect of x_m when $x_{dry} = 0$ is simply:

$$\hat{x}_m = \beta_m, \tag{9}$$

while during load-control periods ($x_{dry} = 1$) the effect becomes:

$$\hat{x}_{m+dry} = \beta_m + \beta_{m\times dry}. \tag{10}$$

In the long-run representation implied by the RECM, the multipliers are given by Eq 11 where ϕ is the adjustment coefficient from the error-correction term.

$$\hat{x}_m^{LR} = -\frac{\beta_m}{\phi}, \qquad \hat{x}_{m+dry}^{LR} = -\frac{\beta_m + \beta_{m\times dry}}{\phi}, \tag{11}$$

Standard errors are then obtained using the delta method. For the short-run combined effect, the variance as in Eq 12.

$$\mathrm{Var}(\beta_m + \beta_{m\times dry}) = \mathrm{Var}(\beta_m) + \mathrm{Var}(\beta_{m\times dry}) + 2\,\mathrm{Cov}(\beta_m, \beta_{m\times dry}). \tag{12}$$

For the long-run effect, the gradient vector of Eq 13 with respect to $(\beta_m, \beta_{m\times dry}, \phi)$ is applied to the variance–covariance matrix of the estimated parameters gives the variance as presented in Eq 14 where ∇g denotes the gradient of $g(\cdot)$

$$g(\beta_m, \beta_{m\times dry}, \phi) = -\frac{\beta_m + \beta_{m\times dry}}{\phi} \tag{13}$$

$$\mathrm{Var}\Big(g(\hat{\beta}_m, \hat{\beta}_{m\times dry}, \hat{\phi})\Big) = \nabla g^{\top}\, \widehat{\mathrm{Var}}(\hat{\beta}_m, \hat{\beta}_{m\times dry}, \hat{\phi})\, \nabla g, \tag{14}$$

E Classification Methodology for Government communication

This appendix details the methodology used to classify government communication regarding energy conservation incentives. The classification follows four main steps: (A) textual preprocessing, (B) semi-supervised labeling, (C) training of a machine learning model using XGBoost, and (D) evaluation of the model's performance.

Step A — Textual Preprocessing

The initial corpus consists of 12,184 political communication extracted from the governmental platform Vie Publique. To prepare the corpus for classification:

- Texts were processed using `SpaCy` (French model), with removal of special characters, stopwords, conversion to lowercase, and lemmatization.
- Texts were transformed into numerical feature vectors using a `CountVectorizer`, followed by a `TfidfTransformer` to enhance informative words.

Step B — Semi-Supervised Labeling and Dataset Construction

communication were labeled semi-supervised as follows:

- **Label 1**: explicit mentions of *sobriété énergétique* or *crise énergétique*.
- **Label 0**: communication clearly focused on unrelated topics (e.g., *jeux olympiques*, *élections*, *violence*, *vaccination*).
- **Label -1**: communication for which no label could be automatically assigned.

Table 16: Distribution of Labeled Data into Training and Testing Sets

Label	Train Set	Test Set
1 (Relevant)	111	51
0 (Non-relevant)	1914	837
-1 (Unlabeled)	9267	-

Given the small size of the initially labeled dataset, a semi-supervised learning strategy was employed to expand the training data iteratively. The general principle is illustrated in Figure 16. Semi-supervised learning was performed by iteratively adding the 10 most confidently predicted examples from the unlabeled set and retraining until no confident examples remained.

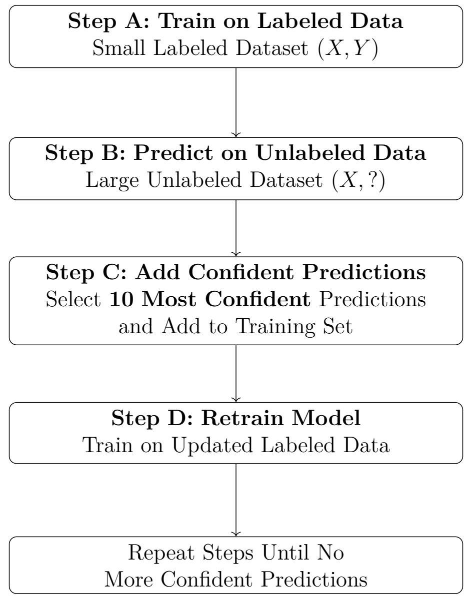


Figure 16: How is a semi-supervised algorithm trained ?

Step C — Training an XGBoost Classifier

A gradient boosting model (XGBoost) was trained, defined by:

$$P(\hat{y}_i = 1|X) = \sigma\left(\sum_{t=1}^{T} f_t(x_i)\right), \quad f_t \in \mathcal{F} \tag{15}$$

where $\sigma(z) = 1/(1+e^{-z})$ is the sigmoid activation function, f_t represents each sequentially learned decision tree, and T is the total number of boosting rounds.

The loss minimized at each iteration is:

$$\mathcal{L}^{(t)} = \sum_i L(y_i, \hat{y}_i^{(t-1)}) + \sum_t \Omega(f_t) \tag{16}$$

with:

- Cross-entropy loss $L(y_i, \hat{y}_i^{(t-1)})$ adjusted for class imbalance via ω_i:

$$L(y_i, \hat{y}_i^{(t-1)}) = -\omega_i \left[y_i \log(\hat{y}_i^{(t-1)}) + (1 - y_i) \log(1 - \hat{y}_i^{(t-1)})\right]$$

- Regularization term $\Omega(f_t)$ penalizing tree complexity:

$$\Omega(f_t) = \gamma K + \frac{1}{2}\lambda \sum_{j=1}^{K} w_j^2$$

Step D — Evaluation of Classification Performance

Model evaluation was conducted on the test set, showing high predictive performance for both topics. For the detection of *sobriété énergétique* communication, the model achieved an accuracy of 99.5%, a precision of 98.0%, a recall of 94.1%, and an F1 score of 96.0%. For the detection of *crise énergétique* communication, the model achieved an accuracy of 99.6%, a precision of 93.4%, a perfect recall of 100%, and an F1 score of 96.6%. These results indicate that the classification process reliably identifies relevant government communication while minimizing false positives and false negatives.

Table 17: Classification Performance Summary

	Sobriété énergétique		**Crise énergétique**	
	True 0	True 1	True 0	True 1
Predicted 0	836	3	859	0
Predicted 1	1	48	4	57
Accuracy	0.995		0.996	
Precision	0.980		0.934	
Recall	0.941		1.000	
F1 Score	0.960		0.966	

Notes: Confusion matrices report counts of correctly and incorrectly classified communication. Metrics are computed on the fully labeled test set.

Discussion

While the classification procedure achieves strong predictive performance, with high accuracy and recall, some limitations must be acknowledged. The initial labeling process relied on specific keywords, potentially reducing the model's ability to capture more implicit or nuanced references to energy conservation. Although the semi-supervised expansion helps mitigate this constraint by enlarging the training set, the final classification remains partly conditioned by the original labeling choices. These limitations are unlikely to significantly affect the detection of explicit government calls for conservation, which are the primary interest of this study. Future improvements could involve replacing the TF-IDF vectorization with word embeddings from pre-trained language models such as CamemBERT. Embedding-based approaches would better capture semantic nuances and context, enhancing the model's ability to classify more subtle or indirect references to energy conservation.