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 substitute for prices or operational measures.

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1 Introduction

A central challenge in economic policy is how to mobilise households to adjust demand when supply-side flexibility is exhausted. Traditional instruments, such as prices, regulation, or subsidies for new technologies, can be effective but often adjust only slowly and may generate inefficiencies, for example, through deadweight loss in 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. While literature has demonstrated that consumer attention is scarce, most empirical evidence comes from small-scale interventions or randomised experiments. Whether large-scale government communication can durably shift household behaviour in real-world crises remains an open question.

This paper provides evidence from the European energy crisis of 2022–2023, and in particular focuses on France, where one of the largest conservation campaigns ever conducted in Europe took place, leading to a natural experiment set up. 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 energy crisis placed unprecedented stress on the French electricity system. Wholesale prices surged, public concern over possible winter power failures intensified, and national attention shifted to energy consumption habits. 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 electricity demand peaks. Demand-side flexibility thus mattered not only for short-term resilience in crisis periods but also for longer-term environmental objectives, by mitigating carbon-intensive back-up generation. In response to this context, the French government launched a nationwide communication campaign urging citizens to reduce their energy use. These efforts ranged from televised appeals to sustained communications promoting low-cost conservation measures, such as lowering indoor heating to 19°C. At the same time, the Minister for Energy Transition, authorised the national grid operator to implement remote load control on certain households equipped with specific electric heating systems. This intervention temporarily reduced their electricity consumption during peak demand periods, directly limiting their capacity for voluntary adjustment.

The goal of this paper is to quantify whether, and through which channels, government communication during the French energy crisis altered household electricity demand by first shaping public attention and then translating that attention into consumption responses.
Two distinct narratives are considered. The first, energy crisis communication, emphasised scarcity and system reliability, seeking to mobilise urgent responses. The second, energy conservation communication, aims to encourage more sustained behavioural change. Distinguishing between these narratives is central: while both were prominent during the crisis, theory and prior evidence suggest that urgency-driven framing may capture attention more effectively than generic conservation appeals, with potentially different implications for household behaviour.

The identification strategy builds on the idea that wholesale electricity prices influence household demand through two distinct channels in France. First, the institutional channel operates via the national regulated retail tariff, which adjusts only with long lags, typically six months or more, and can be decoupled from wholesale prices through ministerial interventions, such as the 2022–2023 tariff shield. A second, faster channel is hypothesised to run through government communication, sharp increases in spot prices are follow by crisis- and conservation-oriented messages that shape public attention and, potentially, household behaviour 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. 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 sets of findings. First, the analysis of attention dynamics shows that public interest in conservation messaging arises only when such messaging is embedded within a broader crisis narrative. In contrast, attention to crisis-related communication responds directly to salient system reliability concerns and peaks during periods of high media coverage about potential shortages. This indicates that the salience of conservation behaviours is conditional on being framed within a scarcity context, whereas crisis narratives can capture attention independently. Second, the consumption analysis reveals that crisis-related attention explained up to 7% of the reduction in electricity, even during load control. Conservation-related attention generates a measurable but delayed reduction in consumption outside control periods, emerging one to two days after the attention shock. However, this effect is absent during control periods, consistent with the mechanical reduction in flexibility caused by remote load-control interventions. However, price and temperature increases exert the largest and most persistent effect on household electricity use, particularly among households on peak/off-peak tariffs. Together, these findings suggest that while communication can mobilise attention, its translation into behavioural change depends critically on both narrative framing and institutional constraints on 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 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 high-frequency 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 speak to the role of public narratives in shaping household behavior under 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 mobilise household responses in 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.[1] 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 consumption while maintaining the same level of service. It typically improves the ratio of

[1](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)

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.[2] 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 7). While the latter limited the full pass-through of market price increases, regulated tariffs nevertheless rose over the period, preserving at least partial incentives for demand reduction. This combination of policies, protecting households

[2]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.

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.[3] 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 *Pour la planète, chaque geste compte*, disseminated across television, radio, and social media.[4,5] 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]

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

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

[5] Given the data currently available, the study focuses on the potential effects of energy conservation incentives stemming from political speeches. At this time, it is not possible to assess the impact of the *Pour la planète, chaque geste compte* media campaign because broadcast data is not available.

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

4 Data

4.1 Data Sources

Data on domestic electricity quantities are obtained from *Enedis* Open Data, the main French distribution system operator. Enedis is a regulated subsidiary of *Electricité de France* (EdF) responsible for managing the low- and medium-voltage distribution grid, covering about 95% of households in mainland France, the remainder being served by local municipal operators. The weather data were collected through the *European Centre for Medium-Range Weather Forecasts* (ECMWF). For prices, regulated tariff are obtained from the open data of the French *Energy Regulatory Commission* (CRE) and spot day ahead prices for France are retrieve via the API from the *entsoe*, the European transparency platform. To examine the relationship between government communication and household energy conservation, public communication recorded by the official repository *Vie publique – Au cœur du débat public* are combined with high-frequency internet search data from *Google Search Volume*, which capture fluctuations in public attention to energy-related narratives over time.

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.

Residential consumers are divided into two main tariff profiles: base and peak/off-peak. Table 2 illustrate the annual electricity consumption patterns for these two profiles. Households with off-peak contracts, who benefit from lower periods 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 (2022–2024), a marked reduction is observed. Overall, residential consumption decreased by 12.2 TWh. This reduction is entirely driven by households with off-peak contracts, who reduced their consumption by 12.5 TWh. In contrast, base profile consumption increased slightly by 0.3 TWh over the same period. However, when the data is 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 also show a modest 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: Consumption variations by tariff

	TWh/year			MWh/contrats/year		
	2019-2021	2022-2024		2019-2021	2022-2024	
Peak/Off-Peak	99.0	86.5	-12.5 (-12.6%)	6.8	5.9	-0.9 (-13.2%)
Base	50.1	50.4	0.3 (+0.6%)	2.9	2.8	-0.1 (-3.4%)
Total	149.2	137.0	-12.2 (-8%)	9.7	8.7	-1.0 (-10.3%)

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 midays, thus different periods are presented: the pre-crisis winters (2019–2021), the first intervention winter (2022), and the second intervention winter (2023). Let us recal that during winter 2022/2023 and winter 2023/2024 grid operator manage at distance heating water system for over 4 millions housing.

Peak/off-peak households display a marked drop in midday consumption during the intervention years. Between 11:00 and 14:00, the load curve for 2022 and 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-tariff 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, Appendix B Figure 11 presents the same daily load profiles 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 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 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

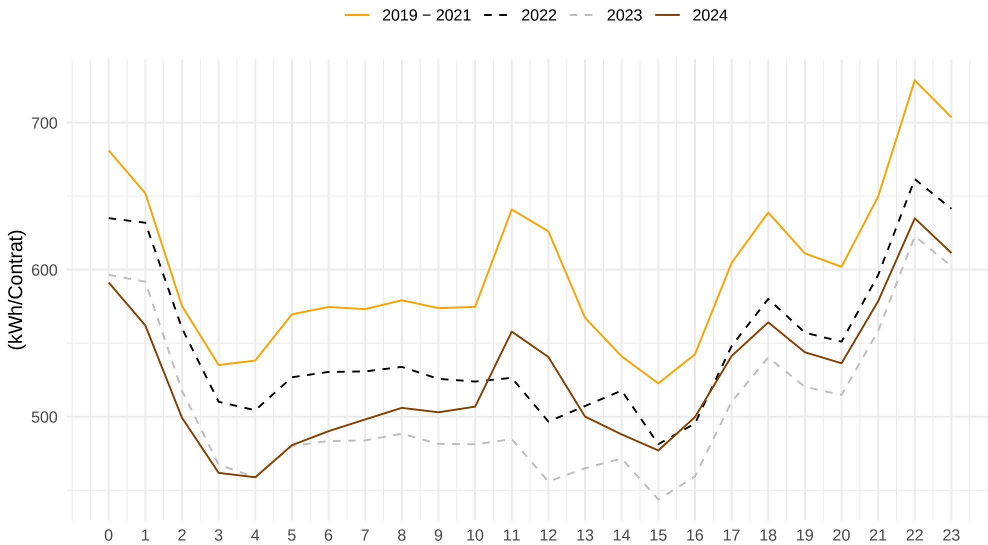


Figure 1: Average hourly load during winter by tarif profile and period

variable pricing based on daily color-coded signals, accounts for only 1% of contracts. Table 4 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: Average share of contracts by profile and power (%)

	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	NA	**19.16**	15.81	6.70	1.00	1.66	0.16	0.05	0.12	44.66
Tempo	NA	NA	**0.70**	0.16	0.03	0.15	NA	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

Notes : In the database, 54% of residential consumers have a base tariff profile, 44% an off-peak profile, and 1% a tempo profile.

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 A Table 6 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:

Table 4: Average share of consumption by profile and power (%)

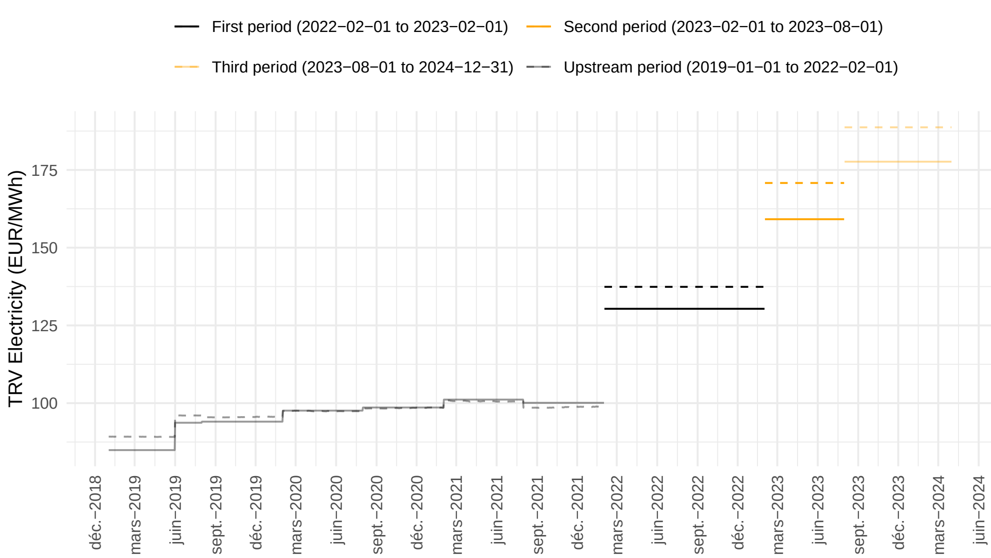
	Power (kVA)									
	3	6	9	12	15	18	24	30	36	Total
Base	1.08	**21.24**	7.07	3.06	0.54	0.97	0.19	0.08	0.33	34.56
Peak/Off-Peak	NA	17.60	**24.94**	13.45	2.28	3.97	0.67	0.24	0.64	**63.79**
Tempo	NA	NA	**0.86**	0.31	0.06	0.32	NA	0.06	0.04	1.65
Total	1.08	**38.84**	32.87	16.82	2.88	5.26	0.86	0.38	1.01	100.00

Notes : In the database, peak/off-peak contracts represent 64% of residential consumption, 34% for base profile, and 2% for tempo profile.

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

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] Appendix B Figure 10 showcase the overall communication time-serie during the sample period. 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 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 D.

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

[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.

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.

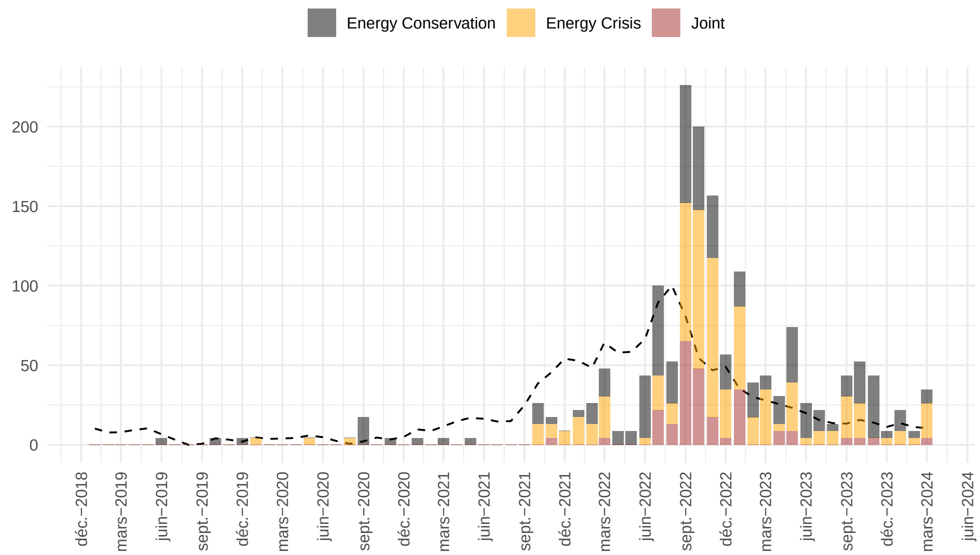


Figure 3: Monthly-frequency government communication from Public Collection

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.

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

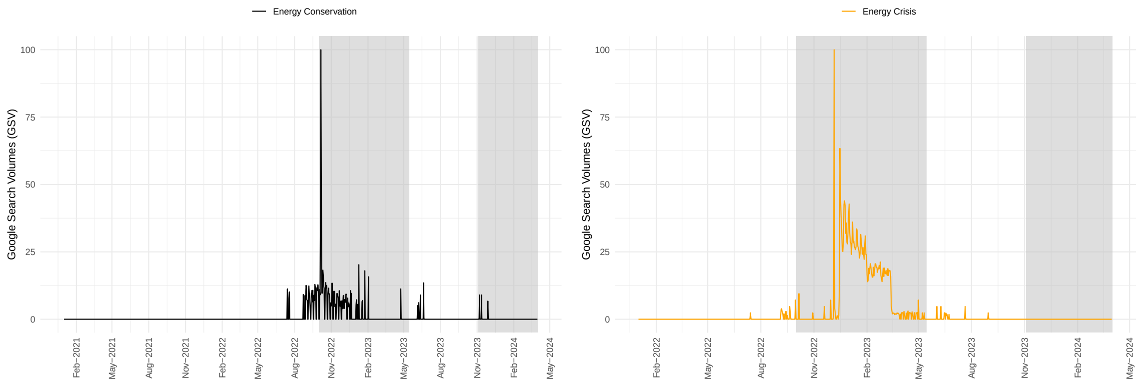
With $g_{k,t,n}$ representing the presence of topic k in the i-th statement on day t, N_t is the total number of communications on day t, and ω_i is a weight reflecting the prominence of the statement. To construct a robust index of government communication, alternative specifications are generated by 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 Google Search Volume

To measure public attention to energy savings narratives, daily Google search volumes (GSV), commonly known as Google Trends, are used for the search terms "*sobriété énergétique*" (energy conservation) and "*crise énergétique*" (energy crisis). 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 (Eichenauer et al., 2022).[8] 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 4 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.

[8] A multi-step reconstruction algorithm is used to build a coherent daily series (2019–2024). 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.



(a) Energy Conservation

(b) Energy Crisis

Figure 4: High-frequency attention index from Google Search Volume

4.6 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, 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.[9] Formally, HDD are calculated according to:

[9] 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).

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

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 B Figure 12 showcases, among other variables, the two pre-adjusted temperature and electricity consumption time-series.

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}). 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 5. 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.

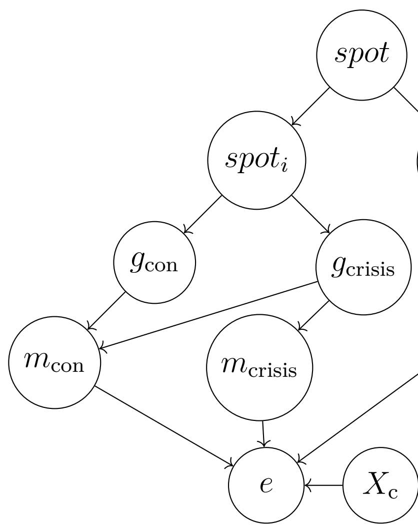


Figure 5: Directed Acyclic Graph (DAG)

5.2 Identifying Government Communication on Public Attention

This section outlines the empirical strategy used to identify the extent to which government communication causally affects 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 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 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.

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

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 $[\hat{\delta}_1, \hat{\delta}_2, \hat{\delta}_3]$ 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.[10] 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.[11]

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):

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

with ϕ_i defined as the speed of adjustment towards the equilibrium relationship, represented in parentheses, and also called the long-term dynamics.[12] 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

[10]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.

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

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

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 B, Table 10). 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 B Table 11 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.

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.

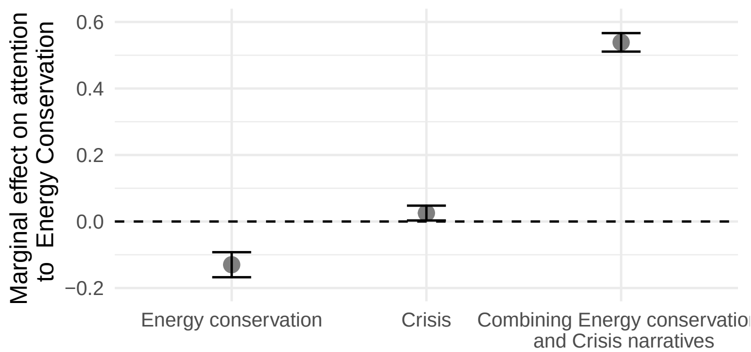
Second, the results, displayed in Figure 6, confirm that government communication meaningfully shapes public attention.[13] First, even if small, attention to the energy crisis is explained exclusively by orthogonalized government communication addressing the crisis, with no detectable effect from conservation-related messages. In contrast, attention to conservation increases significantly only when both conservation and crisis messages are jointly present, and moreoever relatively decrease if communication only about energy conservation is used. These findings strongly suggest that households are most responsive to conservation messaging when it is embedded in a broader narrative of crisis. 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 contextualize 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 B, Table 8 and Table 9). 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.

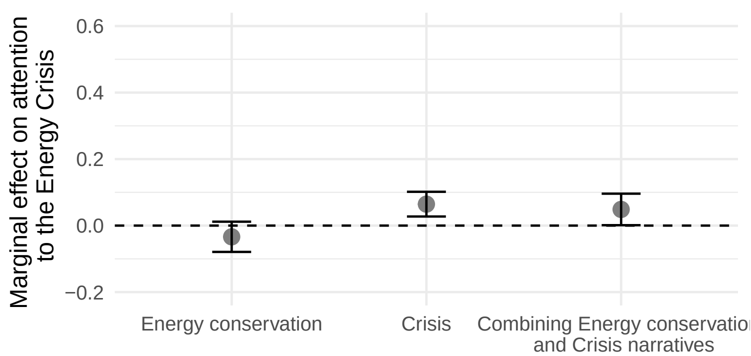
In the case of energy conservation communication, topic clusters are centered on themes such as ecological transition (keywords: "écologique," "transition," "biodiversité"), housing retrofit ("logement," "rénovation," "collectivités"), renewable energy technologies ("hydrogène," "nucléaire," "renouvelables"). These topics reflect the official tone of long-term environmental planning, public sector reform, and sustainability policy. There also exist two meaningfull

[13] The estimates are avaible in Appendix B Table 12

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 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.



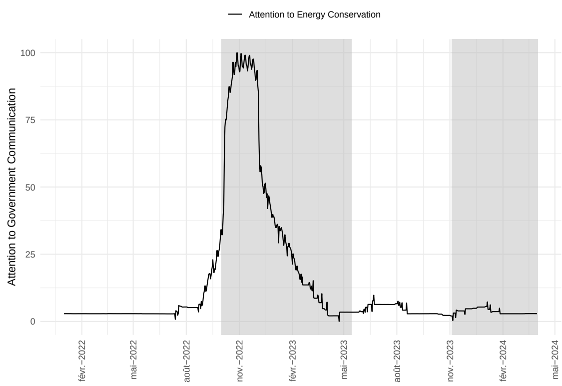
(a) Attention to Energy Conservation



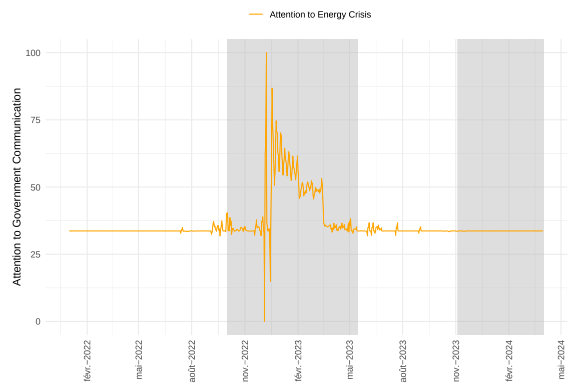
(b) Attention to Energy Crisis

Figure 6: Estimated effects of Government Communication on Public Attention

Finally, Figure 7 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.[14] 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.



(a) Attention to Energy Conservation



(b) Attention to Energy Crisis

Figure 7: Public Attention filtered on Government Communication

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,

[14] 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.

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 8 and in Appendix B, Table 13.

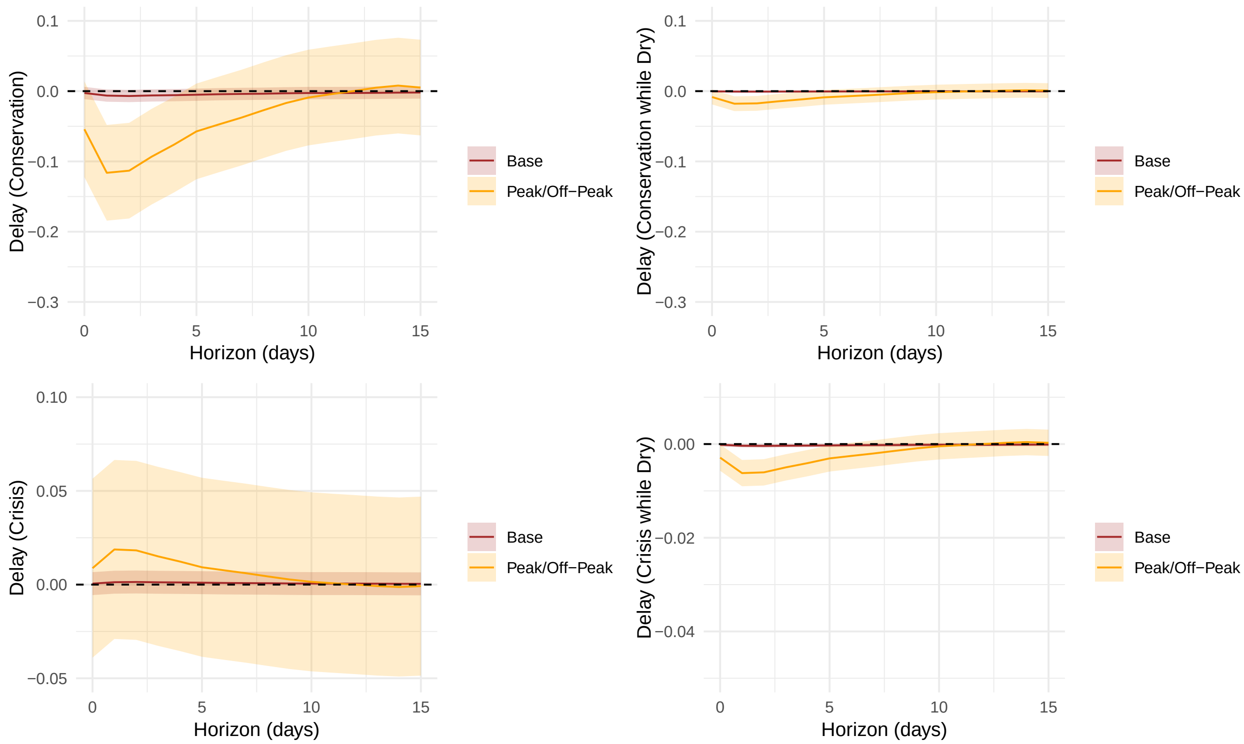
For households on the base tariff, consumption responds most strongly to changes in heating degree days and electricity prices. A 1°C drop in temperature increases daily consumption by roughly 0.024 kWh per contract, while a €1/MWh increase in electricity prices reduces consumption by about 0.003 kWh 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.

In contrast, households on the peak/off-peak tariff display a broader sensitivity to both market and informational shocks. Outside grid-operator control periods, there is no statistically significant short-run response to crisis-related attention. By contrast, conservation-related attention induces a delayed adjustment: consumption begins to fall on day 1 and persists into day 2 after the attention shock. This pattern suggests that, when households are free from remote load control, conservation messaging may prompt short-run behavioural change with a modest lag. During control periods, which also coincide with heightened public discourse framed around energy crisis the pattern reverses. Here, the effect of conservation-related attention is markedly attenuated, while the impact of crisis-related attention is amplified. Two mechanisms likely contribute: the mechanical reduction in available flexibility caused by remote control, which constrains voluntary conservation; and the stronger salience of scarcity framing during these periods, which intensifies the behavioural response to crisis narratives. The attenuation of conservation effects during control periods is also consistent with the possibility that households equipped with remotely controllable heating systems are precisely those that would otherwise be the most flexible.

Quantitatively, a unit increase in an attention index—equivalent to a 1% rise in the share of communication coverage devoted to that theme, is associated with a daily change in average consumption per contract, holding all else constant. For example, a 1% increase in attention to crisis-related communication during a control period is estimated to reduce same-day consumption by 0.003 kWh for a household under a peak/off-peak contract.

6.2.2 Long-run dynamics

Table 5 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.



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 8: Short-Run dynamic estimates

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 0.20% 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 0.21%, 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, when 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 heightened public appeals for energy savings, a 100% rise of public attention to energy crisis messaging, particularly narratives emphasising potential supply shortfalls, is associated with a statistically significant 0.40% decrease in equilibrium consumption. A similar rise of attention to conservation messaging, conditional on concurrent crisis messaging, yields a 0.44% reduction, though the estimate is imprecise and not statistically significant even at the 10% level. This weaker precision may reflect a reduced reservoir of discretionary load, as a substantial share of the group's flexible capacity was already subject to compulsory curtailment. An alternative explanation is that conservation-related appeals may not generate durable behavioral adjustments: attention to conservation could primarily induce short-run responses rather than longer-term learning effects, in contrast with crisis-related narratives that appear to anchor more persistent shifts in consumption. The magnitude of these effects aligns with evidence from Germany, where Jamissen et al. (2024) documents a decrease of 0.9% 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 0.14% 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.

Table 5: 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)		**5.9643*****	0.8600	6.936	0.0000		**15.7462*****	1.4790	10.647	0.0000
x_{pt}	**-0.1432%*****	-0.0100	0.0037	-2.747	0.0061	**-0.2141%*****	-0.0351	0.0069	-5.092	0.0000
x_{HDD}	-0.0131%	-0.0242	0.0705	-0.343	0.7314	**0.2035%*****	0.8523	0.0854	9.984	0.0000
$x_{m(g)_{con}}$	-0.0078%	-0.1424	0.2876	-0.495	0.6206	-0.0149%	-0.6173	0.4708	-1.311	0.1899
$x_{m(g)_{crisis}}$	0.0040%	0.0287	0.2018	0.142	0.8870	0.0062%	0.0996	0.3316	0.300	0.7639
x_{dry}						**-0.0090%****	-0.8129	0.3677	-2.211	0.0272
$x_{m(g)_{con}\|dry}$						0.0114%	0.5222	0.4809	1.086	0.2776
$x_{m(g)_{crisis}\|dry}$						-0.0080%	-0.1326	0.3323	-0.399	0.6900
$x_{m(g)_{con}+dry}$						-0.0044%	-0.0950	0.0729	-1.304	0.1923
$x_{m(g)_{crisis}+dry}$						**-0.0040%***	-0.0330	0.0197	-1.677	0.0936
R^2	0.9917					0.9829				
N	1917					1917				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes : Estimates are expressed in kWh/day/contract, with data from 01/01/2019 to 01/04/2024.

For a representative household under the off-peak tariff, Figure 9 presents the long-run estimates into a more explicit manner. Average annual consumption fell by 0.9 MWh between 2019–2021 and 2022–2024. Of this decrease, 0.49 MWh can be attributed to increases in electricity prices, 0.17 MWh to milder winter temperatures, 0.14 MWh to power cuts operated by the public distributor, and 0.06 MWh (around 7%) to 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.

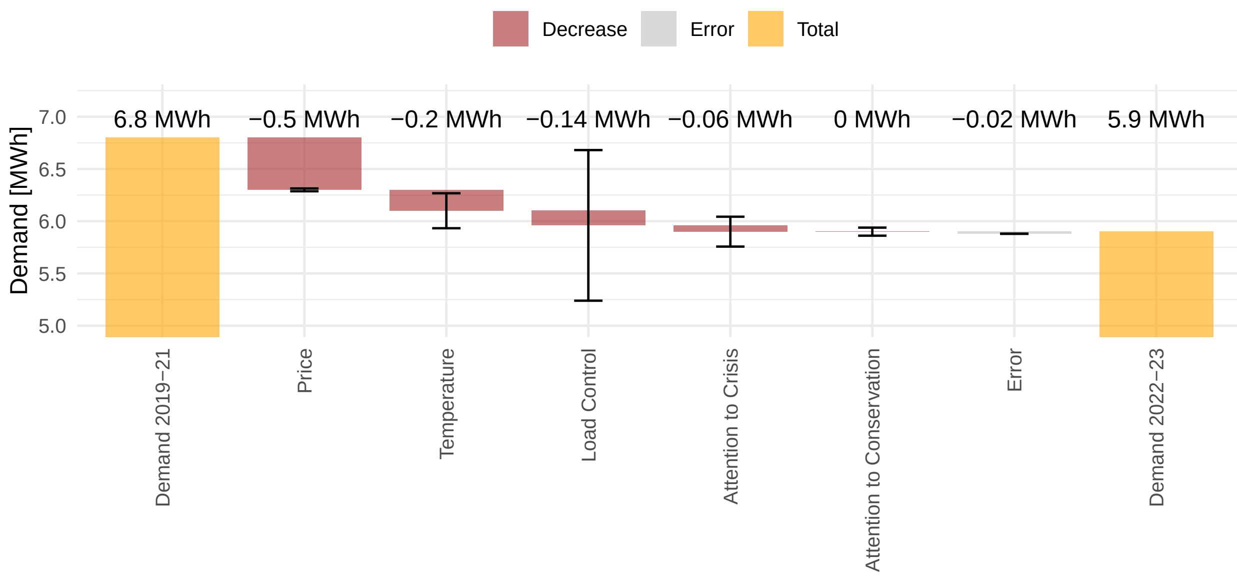


Figure 9: Electricity Decrease Decomposition (Peak/Off-Peak)

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. Crisis-related attention explained up to 7% of the reduction in demand, though its impact was muted when 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 Complementary Background

Table 6: 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 7: 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.

B Complementary Results

B.1 Tables

Table 8: 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 9: 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 10: 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	10	-7.70***	0.01	0.01	10	-15.62***	0.01	0.1
x_{HDD}	4	-11.96***	0.01	0.09	5	-22.64***	0.01	0.1
x_{wind}	3	-14.24***	0.01	0.10	10	-18.88***	0.01	0.1
x_{solar}	1	-19.77***	0.01	0.10	10	-19.87***	0.01	0.1
x_{price}	1	-0.65	0.45	0.01	1	-33.12***	0.01	0.1
$x_{m(g)_{con}}$	9	-3.50	0.34	0.03	8	-11.69***	0.01	0.1
$x_{m(g)_{crisis}}$	8	-4.42	0.68	0.03	10	-5.28***	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 11: 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 12: Estimation of orthogonalised attention to communication

	Dependent variable:	
	Attention m_i	
	Conservation	Crisis
lag(m_i)	0.642***	0.824***
	(0.019)	(0.013)
$\hat{u}_{con}$	−0.130***	
	(0.019)	
$\hat{u}_{crisis}$		0.064***
		(0.019)
g_{joint}	0.539***	0.049**
	(0.014)	(0.024)
g_{con}		−0.034
		(0.023)
g_{crisis}	0.025**	
	(0.011)	
Observations	1,916	1,916
R^2	0.713	0.689
Adjusted R^2	0.713	0.688
Residual Std. Error (df = 1912)	1.907	3.417
F Statistic (df = 4; 1912)	1,189.000***	1,057.000***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 13: 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)		**0.1104*****	0.0248	4.451	0.0000		**1.3838*****	0.1905	7.263	0.0000
x_{pt}	**-0.0440%*****	-0.0031***	0.0009	-3.389	0.0007	**-0.1821%*****	-0.0298***	0.0084	-3.570	0.0004
x_{HDD}	**0.0131%*****	0.0243***	0.0012	20.754	0.0000	**0.0662%*****	0.2774***	0.0088	31.629	0.0000
$x_{m(g)_{con}}$	-0.0001%	-0.0026	0.0053	-0.495	0.6204	-0.0013%	-0.0542	0.0415	-1.307	0.1915
$x_{m(g)_{crisis}}$	0.0001%	0.0005	0.0037	0.142	0.8869	0.0005%	0.0088	0.0291	0.301	0.7638
x_{dry}						**-0.0008%****	-0.0714**	0.0336	-2.129	0.0334
$x_{m(g)_{con}\|dry}$						0.0010%	0.0459	0.0424	1.083	0.2788
$x_{m(g)_{crisis}\|dry}$						-0.0007%	-0.0117	0.0292	-0.399	0.6898
$x_{m(g)_{con}+dry}$						-0.0004%	-0.0084	0.0064	-1.300	0.1937
$x_{m(g)_{crisis}+dry}$						**-0.0004%***	-0.0029	0.0017	-1.690	0.0911
R^2	0.9917					0.9829				
N	1917					1917				

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes : Estimates are expressed in kWh/day/contract, with data from 01/01/2019 to 01/04/2024.

B.2 Figures

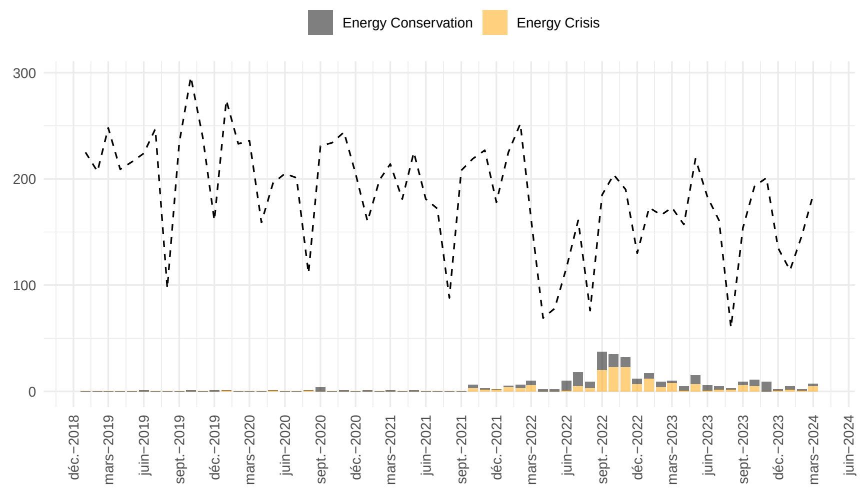

Figure 10: Monthly count of Government Communications

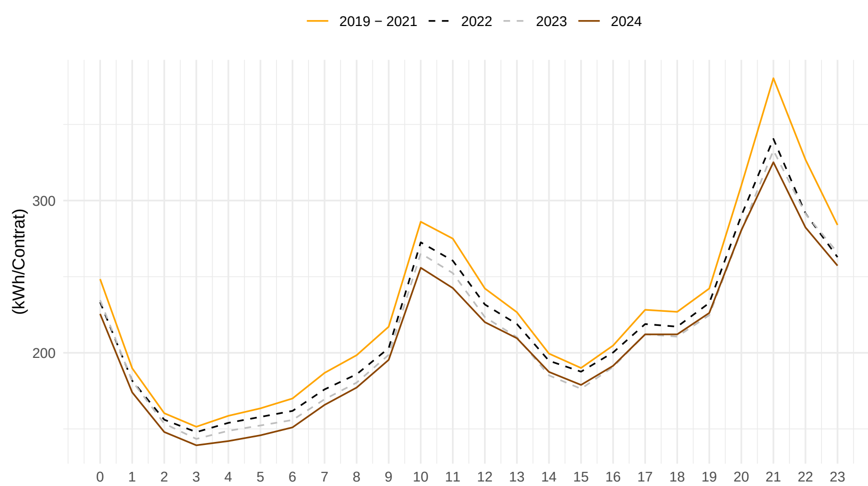

Figure 11: Average hourly load during summer

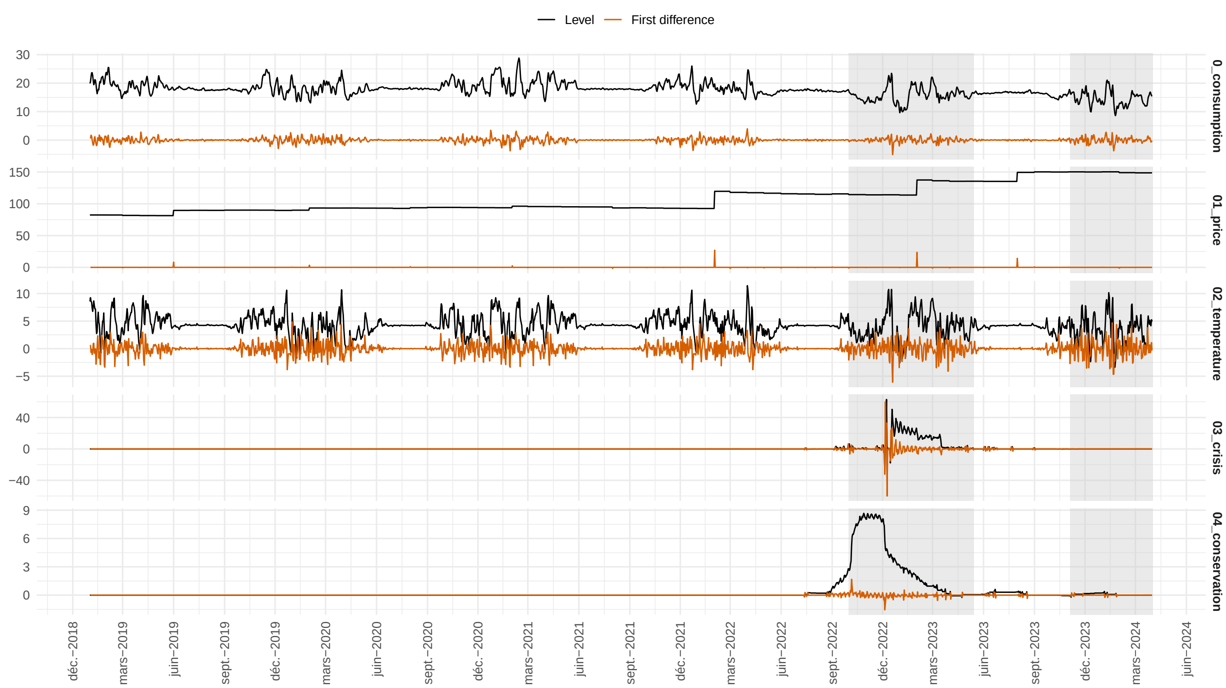

Figure 12: Level and First Difference Main Regressors - Peak/Off-Peak

C 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 $g(\cdot)$

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

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

D 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 14: 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 13. 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.

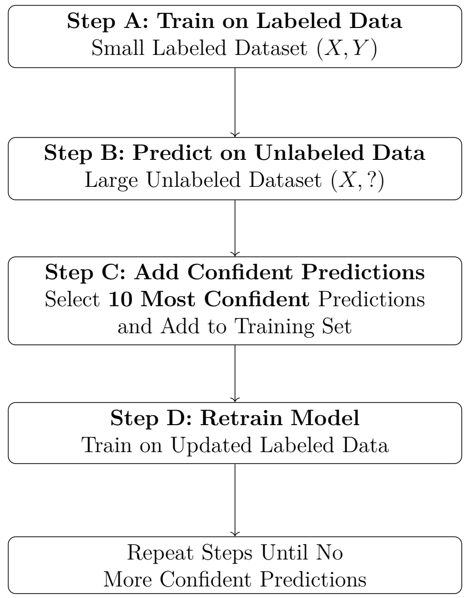

Figure 13: How is a semi-supervised algorithm trained ?

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 15: 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.