Socioeconomic Determinants of Awareness of Energy Labels and Their Influence on Purchase Decisions in the EU

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ERSA working paper 906

May 2025

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Abstract

This paper examines the determinants of individuals' awareness of EU Energy Labels and the extent to which these labels influence their purchase decisions for electric appliances. The analysis is based on Eurobarometer survey data from 27,438 individuals across 28 EU Member States in 2019. Specifically, we explore the role of socioeconomic characteristics such as age, gender, education, financial stability, and political engagement. Our findings indicate that individual characteristics have a stronger effect on the influence of labels on purchase decisions than on label awareness. However, significant heterogeneity across countries persists, even after controlling for individual characteristics. Using our model, we perform three exercises in which we assume a policymaker can either increase label awareness among all unaware individuals or target specific demographic groups. We demonstrate the resulting impact on the share of individuals whose purchase decisions are influenced by the labels. The results reveal that, even when label awareness is at its highest level, it does not necessarily lead to substantially greater influence on purchasing decisions in certain countries.

Keywords: European Green Deal; Ecodesign Directive; Energy-efficiency.
JEL Classification: D12; Q41; Q48; C83

1. Introduction

In response to the urgent need to combat climate change, the European Union (EU) adopted policies in order to achieve carbon neutrality by the middle of this century. The transition to cleaner and more energy-efficient sources is guided by a package of policy initiatives called the European Green Deal. Implementing various directives and regulations, this strategy aims to improve energy efficiency, and eco-design of products.

At the heart of the EU's initiatives to reduce energy consumption in electric appliances and industrial machines are the Energy Labeling Regulation and the Ecodesign Directive. The former requires products to display an energy efficiency label, while the latter sets minimum energy efficiency standards for specific products, excluding less efficient ones from the EU market. Additionally, energy efficiency building standards have been a common policy tool in Europe for over four decades.

The EU's regulations on energy efficiency are crucial, given that end-use energy efficiency could reduce global CO_2 emissions by about 35% by 2050, despite a projected significant increase in the world's GDP. In 2022, EU households contributed approximately 26% of the EU's total final energy consumption. Of this, 13.9% was due to lighting and electrical appliances, while space and water heating comprised 78.4% (Eurostat, 2024). Therefore, it is vital to focus on the adoption of energy-efficient technologies in households and design policies that promote such technologies.

In this paper, we analyze data from a Eurobarometer survey commissioned by the European Commission (EC), which includes responses from 27,438 individuals across 28 EU Member States in 2019. We examine respondents' awareness of the EU energy labeling scheme and its influence on electric appliance purchases using a comprehensive set of demographic variables. Awareness is defined as recognition of the label, while with influence we mean the effects of the label on shaping consumption decisions. We first present a descriptive analysis to explore label awareness and influence at both the national and NUTS levels. Subsequently, we model the probability of awareness of energy labels and the conditional probability of being influenced by these labels when making electric appliance purchases as functions of individuals' socioeconomic characteristics. We then estimate the impact of these characteristics on label awareness and influence using a sample selection model at both the country and NUTS levels. After controlling for individual characteristics, the remaining variation in awareness and influence—attributable solely to geographic factors—is compared with the raw survey data to assess the relative contributions of individual traits and country-specific variables to geographical differences in awareness and influence. Finally, we conduct three counterfactual exercises assuming that a policymaker can increase label awareness to assess the impact on the unconditional probability of the influence of the energy labels on the purchase decisions of individuals.

Our findings reveal that characteristics of the individuals—such as gender, age, education, financial stability, social class, political interest, and recognition of the EU as the

authority responsible for labeling— significantly affect awareness and influence, with a stronger effect on the latter. Specifically, women, middle-aged individuals, and those with higher levels of education are more likely to recognize and consider the EU energy label. In contrast, older adults and students are less influenced by the labels. Middle-class individuals show greater responsiveness to the label, while those with low political interest are less likely to act on it. Moreover, websites are found to be more effective than traditional media in promoting label awareness. Recognizing the EU as the institution behind the label also positively impacts both awareness and influence, underscoring the importance of providing clear information on EU energy policies and initiatives aimed at reducing energy consumption.

Raw survey data reveals geographic variations across the EU, where high label awareness does not necessarily translate into an equally high impact on purchase decisions for almost all countries. The comparison between estimated probabilities and the response shares derived from survey data suggests that, while individual factors significantly influence the extent to which the EU energy label impacts purchasing decisions, their impact on label awareness is limited. The impact of targeted information campaigns aimed at increasing awareness varies across countries, depending on the proportion of individuals they reach. However, our findings reveal that even when label awareness is at its highest level, it does not necessarily translate into substantially higher influence on purchasing decisions in some countries.

The paper is organized as follows. Section 2 reviews the relevant empirical literature. Section 3 describes the historical evolution of energy-efficiency regulations in Europe. In Section 4, we present our data and discuss descriptive statistics for the variables of interest. Sections 5 and 6 introduce our empirical model and present our findings, respectively. In Section 7 we analyze the impact of increased awareness on the adoption of energy-efficient appliances. Finally, Section 8 concludes.

2. Literature Review

The existing literature on energy efficiency labeling for electric appliances is extensive, with a primary focus on their effectiveness, environmental impact, and the design and implementation of related policies. This review specifically examines studies exploring the factors that influence the adoption of energy-efficient appliances.

Empirical studies in this field often rely on data from three main sources. The first group includes observational data, such as residential energy usage monitoring reports and retail sales data for electric appliances. The second group utilizes survey data collected by public and private entities or through questionnaires developed by researchers. The third group of studies relies on experimental data.

Among the first group, several studies aim to assess the determinants of adopting energy-efficient appliances and services across countries. For example, Mills & Schleich

(2012) examines the relationship between household energy usage and household characteristics using data from the Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe (REMODECE) project, which survey households in ten EU countries and Norway. The study finds that households with young children tend to adopt energy-efficient technology more frequently than those with predominantly elderly populations. Furthermore, it identifies a positive correlation between higher education levels and a preference for energy savings for environmental reasons, although this effect varies across countries.

The first group also includes research aimed at assessing the impact of energy policies—such as minimum energy performance standards and labeling schemes—on the adoption of energy-efficient appliances (Bjerregaard & Møller, 2019; Huse et al., 2020; Schleich et al., 2021). For instance, Bjerregaard & Møller (2019) evaluates the quantitative impact of the revision of the EU Energy Label in 2010 on the monthly sales of high- and low-efficiency cold appliances in Danish markets during the period 2005–2017. Their findings indicate that sales of high-efficiency appliances increased by 55% following the announcement of the change and by an additional 42% upon implementation. While the announcement did not affect the sales of low-efficiency appliances, the implementation led to a 45% decrease in online sales of these products.

Additionally, some studies in the first group explore whether the level of information provided on energy labels influences consumers to choose more energy-efficient alternatives. For instance, Houde (2018) analyzes transaction data from the U.S. refrigerator market to evaluate consumer responses to the Energy Star certification—a program which provides a simplified binary rating for energy efficiency rather than detailed energy consumption information. The study incorporates information on refrigerator features and consumer demographics, such as household size, income, education level, homeownership status, type of housing, political orientation, and the age of the household head. The findings suggest that while basic certification can encourage some consumers to consider more energy-efficient options, it may discourage others from seeking more detailed information about energy consumption. Consequently, the overall effect of certification on energy consumption remains uncertain.

In the second group, several studies focus on examining the characteristics that consumers prioritize when purchasing electrical appliances, the differences between consumer profiles, and the factors that influence their purchasing behavior using survey data. For example, Gaspar & Antunes (2011) collect both qualitative and quantitative data through a combination of consumer interviews and surveys. Their findings reveal that consumers consider cost as their most important attribute, followed by quality and energy consumption. These characteristics correlate positively with the consideration of the energy efficiency class in purchase decisions, suggesting that consumers who prioritize these factors are more likely to consider the energy efficiency class.

Using separate binomial logistic regressions, this study also evaluates the influence of

environmental attitudes and pro-environmental behaviors on the probability of considering the energy efficiency class in purchasing decisions. Their findings indicate that positive environmental attitudes do not significantly influence the probability of considering the energy efficiency class. However, independent logistic regression with specific pro-environmental behaviors as predictor variables—such as regularly using energy-efficient light bulbs and rechargeable batteries, separating waste, and avoiding harmful chemicals—reveals a significant positive association between these behaviors and the probability of considering the energy efficiency class. Another research aim of this paper is the identification of consumer profiles. The authors suggest that women are more likely to consider environmental-related attributes such as energy and water consumption, while men tend to focus more on technological innovations, accessories, and the functionality of the appliance. However, gender shows no significant correlation with the consideration of the energy efficiency class. Their findings also indicate that consumers making purchases accompanied by family or friends are more likely to consider the energy efficiency class.

Vázquez et al. (2023) identify consumer segments in Spain through a survey of 3,000 respondents, categorizing groups based on their awareness and attitudes toward certified sustainability labels[1], and the use of these labels in purchase decisions. The study involves twenty-eight certified sustainability labels associated with household products, including electrical appliances, energy, and computing. Using Latent Class Cluster Analysis (LCCA), the study identifies seven distinct segments, in which awareness and attitudes toward different labels varied across product categories. In particular, the consumer uses labels most for electrical appliance and computing categories.The segments are characterized based on the relative importance assigned to environmental concerns—such as climate change, urban pollution, plastic waste, and biodiversity loss—and demographic factors. The findings indicate that young, educated women with strong environmental awareness are the most likely to use certified sustainability labels. However, the study also reveals that nearly half of consumers do not perceive added value in these labels.

Mills & Schleich (2010) investigate the determinants influencing both consumers' knowledge of the energy class and the decision to purchase appliances with energy-efficiency class A using data from a mail survey conducted in Germany in 2002. They perform their analysis across five major kitchen and clothes washing appliances. Their empirical model includes residence and household characteristics and is specified as a Heckman selection model to address potential selection bias arising from consumers' lack of knowledge regarding energy efficiency classes. Their findings for the knowledge of the energy class equation are consistent across appliances, with several factors showing significant effects. However, in the equation describing whether consumers opt for an appliance with energy efficiency-class A, they find fewer significant determinants. In addition, they

[1]In the context of the paper, certified sustainability labels refer to those validated through third-party assessments of a company's adherence to environmental and social standards. These labels, endorsed by certifying entities, are distinguished from self-declarations and advertising claims, which often lack independent verification and scientific rigor.

perform simulations to explore how changes in individual variables affect the estimated probabilities derived from the model. Results indicate that residence characteristics substantially increase the probability of knowing the appliance class for all types of appliances, whereas socio-economic variables have a mixed effect. They find that a consumer is more likely to purchase a class A appliance if she owns other class A appliances for all types of appliances in consideration.

Using an online questionnaire, Brown et al. (2023) examine domestic consumer attitudes and behaviors toward energy in Ireland, considering demographic variables such as province, location, residence type, age, gender, employment status, and annual income bracket. The main findings reveal that most residential energy consumers are concerned about carbon footprints and fossil fuel dependency, with younger individuals expressing greater concern. However, few consumers have adopted low-carbon systems, as high costs remain a significant barrier to adopting energy-efficient technologies.

In several countries, energy labeling schemes have been introduced alongside a variety of incentives to promote the use of energy-efficient appliances. For instance, Wang (2023) examines the influence of an energy-efficiency labeling program in combination with three subsidy schemes in the Chinese refrigerator market, using data from a general social survey. Specifically, the study examines a countryside subsidy designed to promote appliance purchases in rural areas, a trade-in subsidy encouraging the replacement of old appliances, and an eco-product subsidy aimed at promoting energy-efficient products. The findings indicate that both the countryside subsidy and the eco-product subsidy had a positive impact in promoting the adoption of energy-efficient refrigerators, while the trade-in subsidy was less effective.

Several studies have examined the factors influencing the adoption of energy-efficient technologies using survey data collected across multiple countries. The majority of studies that we reviewed are primarily focused on the determinants of purchases of energy-efficient appliances, rather than explicitly assessing the role of labeling schemes in this process. For instance, in independent analyses, Ameli & Brandt (2015) and Krishnamurthy & Kristrom (2015) examine the factors behind consumer choices on energy-efficient technologies in OECD countries. Ameli & Brandt (2015) suggest that the propensity to invest in clean energy technologies is influenced by homeownership status, income level, and consumer attitudes and beliefs. Krishnamurthy & Kristrom (2015) explore the split-incentive problem that arises in the rental housing market. They find large ownership effects, especially for appliances and bulbs, with smaller or no effects for more permanent, location-specific technologies such as solar panels and wind turbines. Within the European Union context, Schleich et al. (2019) investigate the effects of time and risk preferences on the adoption of energy-efficient technologies in eight countries. Their findings indicate that adoption is negatively associated with time discounting, risk aversion, and loss aversion.

In recent years, the third group of studies which uses experimental methods has seen significant growth, particularly those employing Discrete Choice Experiments (DCE). This

research method has become widely used for studying consumer behavior due to its ability to reveal trade-offs consumers make when choosing among multiple alternatives. Most of these studies aim to elicit consumer preferences for energy labels to understand the factors influencing consumer responses to various levels of energy efficiency performance.

For instance, Jain et al. (2018) and Zha et al. (2020) conduct DCEs in India and China, respectively, quantifying the attributes that consumers consider when choosing between two electrical appliances using a mixed logit model specification. Jain et al. (2018) analyze consumer preferences for refrigerators and air conditioners, whereas Zha et al. (2020) focus on refrigerators and washing machines. The first study finds that the proportion of consumers placing a positive value on the highest energy efficiency category was greater for air conditioners than for refrigerators. It also observes that consumers differentiate between energy-efficient categories for air conditioners but not for refrigerators, a finding corroborated by market data. The second study concludes that the energy label program in China is effective, with consumers showing a higher willingness to pay for energy efficiency in refrigerators than in washing machines.

Li et al. (2013) also examine consumers' refrigerator choices using a hypothetical choice experiment. They analyze the influence of a mail-in rebate on consumers' willingness to pay for an Energy Star-labeled refrigerator in the United States. The authors find that offering a rebate creates uncertainty about the quality of Energy Star-labeled refrigerators. Consequently, consumers may be willing to pay less for such refrigerators.

In another study based on a stated-choice experiment involving approximately 3,600 German households, Andor et al. (2019) conclude that willingness to pay for electricity-using durables is influenced by cognitive reflection of consumers—that is, their ability to override automatic, intuitive responses and engage in analytical reasoning. Specifically, the study reveals that consumers with lower cognitive reflection place a lower value on energy efficiency compared to those with higher scores.

The effects of changes in the EU energy efficiency labeling system have also been studied using choice experiments. Specifically, Faure et al. (2021) analyze how the rescaled A-to-G labeling scheme (replacing the previous A+++ to D scheme) affects the valuation of top-rated refrigerators. The results suggest that the rescaled labeling scheme increases valuation when shown alone. However, when displayed alongside the previous scheme, no positive effects are observed from introducing the rescaled labels.

Some experiments have investigated how displayed information influences consumers' willingness to pay for energy-efficient appliances. The literature explores various dimensions, including future energy consumption expressed in monetary terms, the economic value of energy savings, physical energy use, and carbon dioxide emissions. Additional studies have examined factors such as the comparability, quantity, and format of the information provided (Blasch et al., 2019; Davis & Metcalf, 2014; Newell & Siikamäki, 2013; Waechter et al., 2015; Zhou & Bukenya, 2016). For example, Blasch et al. (2019) and Newell & Siikamäki (2013) conclude that presenting information in monetary terms

about future energy consumption or energy savings increases the probability that individuals calculate and select the appliance with the lowest lifetime cost, while the impact of information on physical energy use and carbon dioxide emissions is relatively less significant. In another paper, Zhou & Bukenya (2016) find that willingness to pay for energy-efficient technology increases when information is comparable, more detailed, and refers to significant energy savings.

Based on evidence from randomized field experiments in Kenya, Berkouwer & Dean (2022) identify credit constraints as a significant barrier preventing low-income households from adopting energy-efficient technologies. Furthermore, Park & Woo (2023) suggest that the payback period—the time required to recover the initial costs of energy efficiency investments—affects consumer decisions to invest in energy-efficient home appliances.

In summary, recent literature on energy efficiency labeling primarily aims to explain variations in the impact of labels on consumer purchasing decisions. It does so by analyzing socio-demographic and psychological factors, environmental attitudes, willingness to pay for efficiency, and the complexity and informativeness of labeling schemes. These studies rely on econometric analyses based on market data, surveys, or experimental evidence. While some research demonstrates the effectiveness of energy labels for specific products in particular countries, other studies find no consistent effects.

This body of work has advanced our understanding of the socio-economic characteristics that shape the effectiveness of energy labels. However, most studies focus on single-country analyses. Although a few explore cross-country determinants of energy-efficient technology adoption, they rarely assess the specific role of energy labeling in this process. Our study addresses this gap by using survey data from respondents across all 28 EU Member States. A key contribution is our analysis of geographic variation in both awareness of energy labels and their reported influence on appliance purchases.

Moreover, political factors are largely absent from prior research. It remains unclear how political ideology, participation, or interest at various governance levels affect the success of policies aimed at promoting energy-efficient consumption. Considering these variables may offer critical insights, especially in the dynamic European policy context. In addition, the existing literature emphasizes the impact of energy labels on consumer decisions but devotes less attention to label awareness—a necessary condition for labels to be effective. As highlighted by Schleich et al. (2019), a better understanding of the drivers of both awareness and influence is essential for informing the design of energy-efficiency policies.

Our study contributes by investigating differences in awareness and influence across EU countries, going beyond single-country approaches. We examine how socio-economic and political characteristics relate to these outcomes. Further, we estimate country-specific probabilities of label awareness and influence and compare them with raw survey data. This comparison helps disentangle the contributions of individual-level versus country-level factors to the observed geographic variation. We also conduct three counterfactual

simulations reflecting hypothetical information campaigns aimed at increasing label awareness. We then assess how enhanced awareness affects the likelihood that labels influence purchasing decisions. These exercises yield valuable implications for policy design.

While our study provides new insights, several limitations should be acknowledged. First, the analysis relies on self-reported behavior rather than observed purchasing data, raising concerns about recall and social desirability biases. Second, the Eurobarometer survey does not specify which appliance respondents refer to, preventing product-specific insights. Third, the data do not indicate whether all respondents recently participated in the appliance market. Nonetheless, the survey's broad coverage of EU Member States and inclusion of political variables allows for a cross-national perspective that is rarely explored in this field. Given that our empirical analysis pools data across countries, the estimated coefficients, apart from the country fixed effects, are assumed to be constant across national contexts. Therefore, the predicted probabilities and simulation outcomes should be interpreted with this limitation in mind.

3. Energy efficiency label regulations in Europe

The EU is committed to advancing an Energy Union to support its climate goals, as demonstrated by initiatives such as the European Green Deal, which aims for climate neutrality by 2050 (European Commission, 2019b). Due to its moderating effects on energy demand, policies aiming to increase the energy efficiency of the appliances in the marketplace are a crucial element in this endeavor. A key aspect of the EU's energy efficiency strategy is Energy Labeling, which enables consumers to make informed appliance choices based on energy consumption, while also motivating manufacturers to develop more energy-efficient products.

The current energy labeling framework in the EU evolved from proposals dating back to the 1990s (Schleich et al., 2021). The first energy labeling initiative emerged in 1992 introducing seven energy efficiency classes from A to G, with A in green color representing the best energy performance and G in red color the worst (European Council, 1992). Directives gradually implemented labeling for refrigerators, freezers, and their combinations (European Commission, 1994; European Parlament and European Council, 1996), washing machines (European Commission, 1995), and dishwashers (European Commission, 1997).

In 2003, Directive 2003/66/EC (European Commission, 2003) introduced classes A+ and A++ to address substantial differences in energy efficiency among appliances within the highest class. These discrepancies arose from the energy efficiency improvements seen in certain products.

Seven years later, Regulation (EU) 1060/2010 established A+++ as a new energy efficiency class and revamped the label display, assigning different shades of green to each A class. Additionally, a new Energy Efficiency Index (EEI) was introduced, leading to

the rescaling of energy efficiency classes. For instance, the EEI for refrigerating household appliances was defined as a metric comparing the Annual Energy Consumption of a tested household refrigerating appliance to its Standard Annual Energy Consumption based on factors such as storage volume and type of appliance (European Commission, 2010).

Ecodesign legislation, such as Directive 2009/125/EC (European Parlament, 2009) and Regulation (EU) 2016/2282 (European Commission, 2016), complement energy labeling by setting mandatory minimum requirements for energy performance and material use throughout a product's lifetime. Thus, Ecodesign requirements aim to force out the least efficient energy-related products from the EU and European Economic Area (EEA), while energy labeling classifies the products permitted for sale to influence consumer choices towards options that offer greater energy savings (European Commission, 2024).

Nowadays, the energy labeling regulation is framed by Regulation (EU) 2017/1369, which maintains the same scope as Regulation (EU) 1060/2010 while enhancing provisions for the accuracy and comparability of label information (European Commission, 2017). The updated regulation returned to a simpler A-G scale with an initially empty A class allowing room for future improvements in energy efficiency. For instance, an electric appliance previously graded A+++ could now be classified as a C class appliance, even though it is just as energy efficient as before. These updated labeling adjustments entered into force in 2021 for five product groups such as fridges and freezers, dishwashers, washing machines and washer-dryers, electronic displays, and lighting (European Commission, 2019a).

Furthermore, the regulation introduced the European Product Registry for Energy Labeling (EPREL), a new database where manufacturers and importers must register their products and provide detailed technical documentation for compliance monitoring endeavors. This central database enhances market oversight and facilitates digital access to energy labels and product information (European Commission, 2017).

The new labels for the product groups mentioned above display a QR code with a link to EPREL, along with a few other elements: energy efficiency class information, energy consumption, and additional non-energy parameters (i.e. noise emissions, water consumption, capacity, repairability or reliability class, etc.).

The decision-making process for designing policies to advance the use of energy-efficient products is a participatory process involving stakeholders (including industry, consumer organizations, environmental NGOs, etc.) and EU Member States. It involves consultations with stakeholders, expert discussions on the impacts of measures, and final scrutiny by the European Parliament and Council (European Commission, 2019a).

4. Data

The present study uses data from Eurobarometer 91.4, a survey conducted by the European Commission across the member states of the EU. The survey relied on a multistage

sampling procedure to select 27,438 respondents aged 15 years and older, who underwent face-to-face or computer-assisted interviews between May 9th and May 25th, 2019.

The survey consisted of three modules focusing on European attitudes towards trade and EU trade policy, EU energy policy, and discrimination within the EU. The variables most relevant to this study are derived from the second module, which examines respondents' perspectives on various aspects of the EU energy policy. These include the EU's responsibilities in energy-related matters, awareness of the EU Energy Labeling scheme, the influence of the EU Energy Label on the purchase of electric appliances, and priorities for EU energy policy over the next decade. Additionally, the study incorporates relevant variables from other modules, such as respondents' main sources of information and internet usage, allowing us to analyze how exposure to different media channels influences label awareness. A set of demographic variables from the survey data is also included in the analysis.

4.1 Definition of key variables

This study focuses specifically on responses to two questions in the Eurobarometer 91.4 survey. The first variable of interest measures respondents' awareness of the EU Energy Label, which is a prerequisite for assessing its influence on appliance choices. The second variable records whether the EU Energy Label influenced respondents' appliance purchases. Table 1 lists the permissible responses for the original version of these two questions.

These questions were transformed into binary variables with *1* denoting *yes* and *0* representing *no*. It is important to note that the *no* category includes the cases where the respondents stated that they *do not know* (DK) for both questions. Additionally, for the second question, respondents who did not recognize the EU Energy Label and thus for whom the question was marked as "not applicable" were also classified under the *no* category.

Table 1: Admissible answers for key variables

Variable	Question	Values	Description
(1)EU Energy Label Awareness	Do you recognise the following label? One answer only.	1	Yes, and you know what it stands for
		2	Yes, but you don't know what it stands for
		3	No, you have never seen it
		4	Do not know (DK)
(2)EU Energy Label Influenced Choice of Electric Appliances	Did the EU energy label influence the choice of your purchase of electric appliances (fridges, washing machines, dishwashers, televisions...)? One answer only	1	Yes, it has helped you purchase a more energy-efficient appliance, your main reason being to save money
		2	Yes, it has helped you purchase a more energy-efficient appliance, your main reason being to select more environmentally friendly appliances.
		3	Both (to save money and to select more environmentally friendly appliances)
		4	No, it has not influenced your purchase choice
		5	Do not know (DK)
		9	Inapplicable (not 1 or 2 in EU Energy Label Awareness)

We incorporate socioeconomic variables such as gender, age, education, marital status, number of children, difficulties in paying bills during the last year, social class self-assessment, size of community, left-right political placement, political interest, country, NUTS codes, and NUTS levels in our study.[2] All of these variables are categorical, with some recoded by clustering broader categories with similar implications into a common group.[3] The variables age and number of children were converted from numeric to categorical formats. Additionally, the NUTS codes and NUTS levels were recoded to standardize NUTS level 1 regions across all countries, as the survey measured countries at varying NUTS levels. Upon code verification, it was determined that the NUTS classification compatible with all countries in the survey corresponds to the 2010 version.

Additionally, four other variables related to the EU energy policy module were examined. The first variable measures the extent to which respondents agree that the EU should facilitate consumers' choice of energy sources and suppliers. The second variable assesses whether respondents associate energy policy with reducing energy consumption across the EU, such as insulating homes or purchasing energy-efficient products. The third variable captures respondents' views on the importance of clear information as a priority for the EU's energy policy over the next decade. Finally, we consider the answers of individuals on the institution they think is responsible for the energy label, including the EU, national governments, industry and private businesses, and consumer organizations.

In our analysis of the determinants of individual awareness of the EU energy label, we include two additional variables. The first is the *Main Information Sources* variable,

[2]The Nomenclature of Territorial Units for Statistics (NUTS, from the French *Nomenclature des Unités Territoriales Statistiques*) is a geographical classification that divides the economic territory of the European Union (EU) into regions at three levels: NUTS 1, 2, and 3, moving from larger to smaller territorial units. Above NUTS 1 is the *national* level of the Member States. The NUTS is governed by Regulation (EC) No 1059/2003 of the European Parliament and Council (26 May 2003) and is regularly updated. Source: Eurostat.

[3]For instance, in the case of social class, we bundled the responses *Other*, *None*, *Don't Know (DK)*, and *Refusal (Ref)* into a single category.

which identifies where respondents primarily obtain information about globalization and international trade, serving as a proxy for the channels through which they access general information, including energy efficiency policy. The response categories *Other*, *None* and *DK* were combined into a single category. The second variable, *Internet Use*, measures the frequency of respondents' internet access.

As we demonstrate below, even after controlling for observable differences, substantial heterogeneity remains across countries in terms of awareness and influence of the labels. To explain these country-specific differences in label awareness and influence, we incorporate additional data from Eurostat, the OECD and the Manifesto Research on Political Representation project (MARPOR).

4.2 Descriptive analysis

We begin our analysis of the survey data by calculating the percentage of respondents in each country who reported being aware of the EU Energy Label, which we refer to as the *awareness level*. Among those who indicated awareness, we then calculate the percentage of individuals who reported being influenced by the label in their purchasing decisions for electric appliances. The resulting variable is referred to as the *influence level*. Figure 1 shows the awareness level across the 28 EU Member States with an EU-level average of 90.81%.

We have classified the countries in the dataset into two groups based on the average awareness level: above-average (AA) and below-average (BA) countries. The above-average group consists of fifteen countries, with the Netherlands having the highest percentage of respondents aware of the label, closely followed by Luxembourg, Germany, and France. The below-average group comprises thirteen countries, primarily from Eastern and Southern Europe. Notably, Cyprus, Lithuania, Malta, and Greece have the lowest awareness levels of the EU Energy Label.

Figure 1: Awareness Level of the EU Energy Label Across Countries

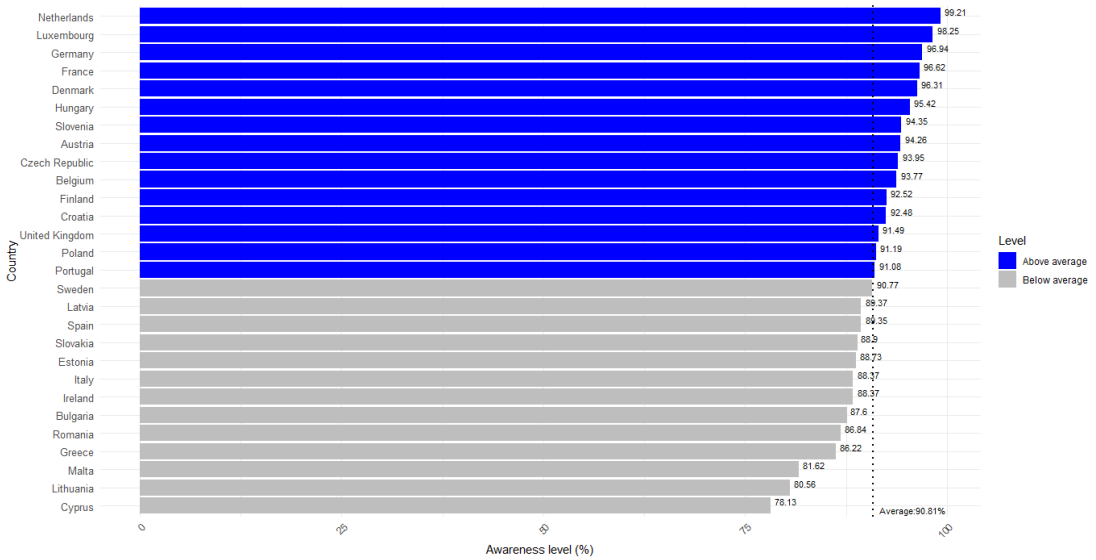


Figure 2: Influence Level of the EU Energy Label on Electric Appliance Choice Across Countries

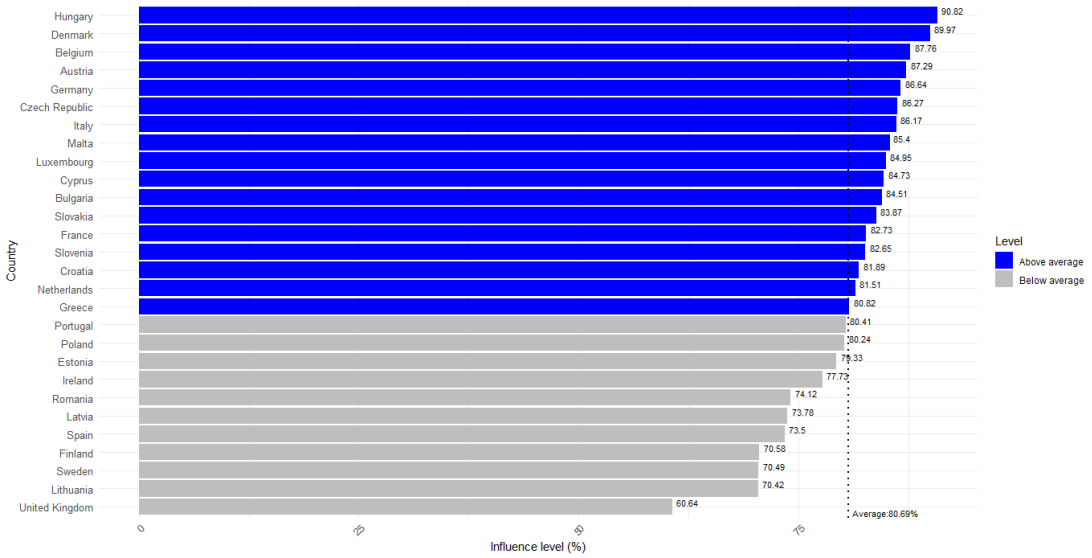


Figure 2 presents the influence level in each of the 28 EU Member States, with the EU average standing at 80.69%. Similarly, we have classified the countries into above-average (AA) and below-average (BA) groups based on this measure. In this case, the above-average group includes seventeen countries, and the remaining eleven countries form the below-average group. The ranking of countries in terms of their level of influence differs from their ranking based on their awareness levels. There is no clear pattern separating Western, Eastern, and Southern Europe. The top countries are Hungary, Denmark, Belgium, and Austria, while the bottom countries are the UK, Lithuania, Sweden, and Finland.

Table 2 presents the summary statistics of the variables used in the empirical analysis for the AA and BA country groups defined earlier. The distribution of most socio-demographic variables is similar for both groups regarding both awareness and influence. However, there are notable differences, such as in the variable *Difficulties paying bills*, where the proportion of individuals reporting frequent difficulties in paying bills is higher in the below-average awareness group than in the above-average awareness group. In contrast, the opposite pattern is observed for influence.

Figure 3a presents the awareness level of the EU label by NUTS regions, where darker shades correspond to higher levels of awareness. The regions with the highest levels of awareness are located in Germany (5 regions), the Netherlands (4 regions), and one region in France (Est). In contrast, the regions with the lowest levels of awareness are more spread across Europe, including areas in Belgium, Italy, Malta, Poland, Greece, Lithuania, Romania, Spain, and Cyprus.

Table 2: Descriptive statistics for key variables by country groups (%)

Variable	Category	Sample	Influence		Sample	Awareness	
			AA	BA		AA	BA
(1)EU Energy Label - Awareness	Never see it + DK	0	0	0	2,416	5.51	12.9
	Yes	25,022	100	100	25,022	94.49	87.1
(2)EU Energy Label - Influence	No + DK + Never seen it	4,828	14.73	26.26	7,244	22.09	31.77
	Yes	20,194	85.27	73.74	20,194	77.91	68.23
(3)Gender	Man*	11,483	46.59	44.83	12,492	46.18	44.72
	Woman	13,539	53.41	55.17	14,946	53.82	55.28
(4)Age	15 - 22 years*	1,714	6.83	6.88	1,874	6.91	6.73
	23 - 38 years	5,355	21.19	21.72	5,570	20.62	19.91
	39 - 54 years	6,750	27.81	25.71	7,083	25.78	25.86
	55 - 73 years	8,803	35.47	34.73	9,738	35.55	35.42
	74 years and older	2,400	8.7	10.95	3,173	11.15	12.08
(5)Age when stopped education	Up to 15 years*	2,845	10.74	12.33	3,615	12.55	13.95
	16-19 years	11,009	46.58	40.06	11,973	42.54	45.01
	20 years and older	9,099	34.35	39.44	9,537	36.09	33.1
	Still Studying	1,549	6.42	5.84	1,676	6.3	5.87
	No full-time education	204	0.95	0.6	250	1.26	0.47
	Ref + DK	316	0.96	1.73	387	1.26	1.6
(6)Marital Status	(Re-)Married*	13541	54.87	52.97	14,673	51.63	55.78
	Living with partner	3,160	12.94	12.15	3,321	13.59	10.25
	Single	3,993	16.06	15.81	4,314	16.04	15.33
	Divorced or separated	2065	7.93	8.74	2,243	8.91	7.26
	Widow	2,113	7.61	9.71	2,712	9.16	10.78
	Ref + Other	150	0.59	0.62	175	0.68	0.59
(7)Number of children	None*	18,758	75.5	74.15	20,843	75.96	75.97
	One	3,122	12.15	12.97	3,296	11.75	12.34
	Two	2,411	9.87	9.28	2,514	9.58	8.65
	Three	505	1.76	2.41	537	1.98	1.93
	Four or more	226	0.71	1.19	248	0.74	1.11
(8)Difficulties paying bills	Most of the time*	1,718	7.7	5.59	2,054	5.31	10.19
	From time to time	5,835	24.08	22.17	6,538	18.8	30.09
	Almost never/never	17,124	66.5	71.39	18,467	74.43	58.43
	Ref	345	1.73	0.85	379	1.46	1.28
(9)Social class	Working class*	6,252	20.91	31.21	7,233	23.54	29.87
	Lower middle class	3,723	15.05	14.62	4,070	15.39	14.14
	Middle class of society	12,193	52.09	43.61	13,068	48.35	46.73
	Upper middle class	1,824	8.28	5.77	1,889	8.64	4.7
	Higher class	147	0.59	0.59	157	0.76	0.34
	Other+None+Ref+DK	883	3.08	4.21	1,021	3.33	4.21
(10)Size of community	Rural area*	7,017	27.03	29.59	7,840	26.84	30.74
	Small urban area	8,072	35.19	27.79	8,831	34.92	28.78
	Large urban area	9,933	37.78	42.63	10,767	38.25	40.48
(11)Left-right political placement	Left*	6,541	27.99	23.33	7,082	28.06	23.01
	Centre	8,551	33.9	34.59	9,313	35.31	32.23
	Right	5,834	23.08	23.67	6,354	23.15	23.16
	DK/Ref	4,096	15.03	18.41	4,689	13.47	21.59
(12)Political interest index	Strong*	4,356	18.07	16.4	4,644	16.85	17.03
	Medium	12,723	52.19	48.8	13,701	50.41	49.34
	Low	3,999	16.32	15.46	4,387	16.4	15.47
	Not at all	3,944	13.42	19.33	4,706	16.34	18.16
(13)Facilitate energy choice	Totally agree*	13,304	52.63	53.99	14,429	49.77	56.1
	Tend to agree	9,030	36.39	35.62	9,929	37.81	34.17
	Tend to disagree	1,512	6.44	5.44	1,648	6.95	4.84
	Totally disagree	458	2.07	1.46	496	2.27	1.24
	DK	718	2.47	3.48	936	3.21	3.67
(14)Purchasing energy-efficient products	Not mentioned*	17,716	67.57	75.73	19,614	69.52	73.93
	Mentioned	7,306	32.43	24.27	7,824	30.48	26.07
(15)Energy issue: clear information	Not mentioned*	18,425	73.13	74.41	20,294	73.89	74.05
	Mentioned	6,597	26.87	25.59	7,144	26.11	25.95

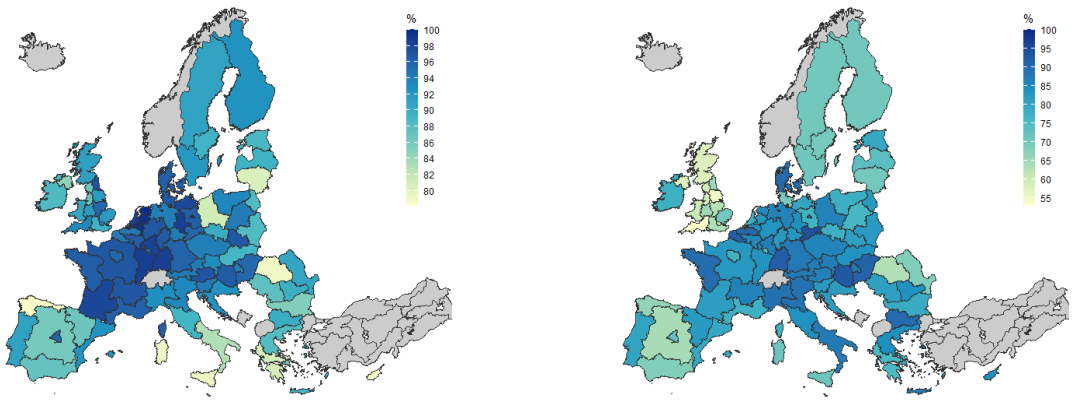
Table continues on the next page

Table 2: (Continued) Descriptive statistics for key variables by country groups (%)

Variable	Category	Sample	Influence		Sample	Awareness	
			AA	BA		AA	BA
(16)EU Energy Label - Responsibility	The government*	2,045	9.13	6.71	2,218	9.69	6.09
	The European Union	12,990	52.96	50.32	13,479	48.95	49.35
	Industry	2,884	10.74	12.72	3,036	9.14	13.47
	Consumer organisations	2,827	12.64	9.25	2,987	13.35	7.82
	DK	4,276	14.52	21.01	5,718	18.88	23.28
(17)Main information source	TV*	10,696	43.4	41.75	12,059	43.35	44.7
	Newspapers/magazines	2,971	12.62	10.73	3,167	14.43	7.95
	Radio	1,114	4.13	4.94	1,245	4.32	4.81
	Internet websites	5,619	21.63	23.72	5,794	21.26	20.94
	Online social networks	2,071	8.09	8.56	2,185	6.99	9.17
	Close ones	1,154	4.99	4.04	1,278	4.5	4.85
	Other + None + DK	1,397	5.13	6.27	1,710	5.16	7.57
(18)Internet use	Everyday/almost everyday*	18,970	75.43	76.4	19,900	75.72	68.55
	Often/sometimes	2,431	10.68	8.24	2,649	9.78	9.5
	Never/no access	3,213	11.99	14.14	4,311	12.76	19.39
	No Internet access at all	408	1.9	1.22	578	1.74	2.56

The numbers in the AA (Above-Average) and BA (Below-Average) columns represent percentages.
* denotes the reference category for each variable in the models discussed in Section 6.1.

Figure 3: Awareness and Influence Level of the EU Energy Label by NUTS Regions Level 1



(a) (b)

Map lines delineate study areas and do not necessarily depict accepted national boundaries.

Figure 3b shows the influence level of the EU energy label on purchasing decisions at the NUTS level 1. Among the top ten regions, four are in Germany, two in Hungary, and one in France, Belgium, Bulgaria, and Denmark. In contrast, among the ten regions with the lowest percentage of respondents who reported being influenced, nine are in the United Kingdom, and one is in Romania. Notably, the South West England region in the United Kingdom has the lowest reported percentage of influence within the EU, at 53.01%.

5. Econometric Model

In this section, we examine the determinants of individuals' awareness of the EU Energy Label and their responses regarding the label's influence on their decision-making. In the dataset, responses about whether the label influenced individuals' purchases are only recorded for those who reported being aware of the label. Therefore, we consider a two-stage Heckman selection model as an appropriate framework to simultaneously analyze the determinants of awareness and influence. Respondents indicate whether they recognize the EU Energy Label in the first stage. In the second stage, individuals aware of the label report whether it influenced their choice of electric appliances. As noted earlier, both questions are coded as binary variables after transforming the original responses.

The first stage *awareness* (selection) *equation* is specified as follows:

$$s = \begin{cases} 1 & \text{if } \mathbf{X}\alpha + \nu \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $s = 1$ indicates that an individual reports being aware of the EU Energy Label. We aim to explain this response using a set of socio-economic characteristics of the respondents, which have been converted to categorical variables as discussed earlier. These variables are denoted by X, and ν represents unobserved consumer characteristics.

The *influence equation* is specified similarly as:

$$y = \begin{cases} 1 & \text{if } \mathbf{Z}\beta + \varepsilon \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $y = 1$ indicates that the respondent reported being influenced in their purchase decisions for electric appliances by the EU Energy Label. We aim to explain these responses using a vector of categorical variables $\mathbf{Z}$, which represent the socio-economic characteristics of the respondents. The unobserved respondent characteristics are denoted by ε. We assume that ε follows a standard normal distribution and satisfies the condition $E(\varepsilon|\mathbf{Z}) = 0$.

Assuming that the error terms from both equations, ν, and ε, follow a multivariate normal distribution, and exploiting the fact that the error term ε can be decomposed into the sum of two terms and written as $\varepsilon = \rho\lambda(\mathbf{X};\hat{\alpha}) + \omega$, where ω has a zero mean conditional on Z by construction, we can write:

$$E(y|Z, s = 1) = \mathbf{Z}\beta + \rho\lambda(\mathbf{X};\hat{\alpha}) \tag{3}$$

where $\lambda(\mathbf{X};\hat{\alpha})$ denotes the hazard function (inverse Mills ratio), which can be written

using the estimates from the first stage model as follows:

$$\lambda(\mathbf{X};\hat{\alpha}) = E(\nu|\mathbf{X}\alpha > -\nu) = \frac{\phi(\mathbf{X}\hat{\alpha})}{\Phi(\mathbf{X}\hat{\alpha})}. \tag{4}$$

Thus, we estimate the following *influence equation* in the second stage:

$$y = \begin{cases} 1 & \text{if } \mathbf{Z}\beta + \rho\lambda(\mathbf{X};\hat{\alpha}) + \omega \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The vector of variables included in the *awareness equation* $\mathbf{X}$ includes all the variables from the *influence equation* $\mathbf{Z}$ and two additional variables about the main information source of the respondents and their internet use. We assume that these variables impact *awareness* but not *influence* giving us the necessary exclusion restrictions required for identification of the model.

The models specified in Equations (1) and (2) are also estimated independently, ignoring the connection between them, using a simple probit model allowing us to assess the importance of the corrections for sample selection bias that should arise due to our use of the Heckman methodology.

6. Empirical Results

This section presents the results of the estimation of the Heckman sample selection model, structured into two parts. First, we discuss the coefficient estimates for the characteristics determining label awareness and influence on purchase decisions of electric appliances. Second, we use the model to compute country-specific probabilities of label awareness and influence (conditional on awareness), holding all other categorical variables at their baseline levels. We then compare the estimated probabilities with the levels of both awareness and influence at the country level based on raw data. This exercise allows us to isolate the role of socioeconomic and demographic variables in explaining the variation across countries.

6.1 Determinants of Energy Label Awareness and Influence

In Table 3, we present the estimates from the Probit models in columns three and four, and the estimates from the Heckman sample selection model in columns five and six.[4] The coefficients for categorical variables are interpreted relative to their reference levels, as indicated by a star in Table 2. Both models include country-fixed effects. Table A.1 in the Appendix provides the estimates of the Heckman sample selection model with NUTS region-level fixed effects. The results are comparable to the model with country-fixed

[4]To evaluate potential multicollinearity, we assessed the pairwise correlations among the independent variables included in our models. The analysis does not indicate the presence of high correlations.

effects, which we discuss below.

The significant estimate of ρ indicates that unobserved factors influencing label awareness also affect label influence, thereby supporting the use of the Heckman specification. We report the estimates from Probit models along with the estimates from our Heckman model in order to illustrate the effects of the Heckman correction on the estimates.

The Probit model indicates that women are more likely to recognize the label, whereas the estimates in the sample selection models are positive but not statistically significant. Nevertheless, across both models, being a woman significantly increases the likelihood of being influenced by the label when making purchasing decisions.

Individuals aged between 23 and 54 years are consistently found to be significantly more likely to be aware of and influenced by the label across all models. In contrast, older age groups (74 years and older) are significantly less likely to be aware of and influenced by the label in the Probit model. However, in the Heckman model, the negative effect of older age is significant only in the influence equation.

Individuals with 16 or more years of education are more likely to recognize and be influenced by the label. Conversely, those who are still studying are estimated to have a lower likelihood of being influenced. This category likely encompasses a diverse group, ranging from young students in school to individuals pursuing advanced degrees, such as doctoral programs.

Table 3: Estimates of the Probit and Heckman Sample Selection Models

Variable	Category	Probit		Heckman Country	
		Awareness	Influence	Awareness	Influence
(3)Gender	Woman	0.0489*	0.1104***	0.0382	0.1005***
		(0.026)	(0.020)	(0.026)	(0.020)
(4)Age	23 - 38 years	0.1823**	0.1345***	0.1738**	0.1194**
		(0.075)	(0.052)	(0.075)	(0.051)
	39 - 54 years	0.1579**	0.2475***	0.1483*	0.2384***
		(0.080)	(0.056)	(0.079)	(0.055)
	55 - 73 years	0.0146	0.0415	0.0151	0.0626
		(0.083)	(0.058)	(0.082)	(0.056)
	74 years and older	-0.3166***	-0.2054***	-0.2984***	-0.0940
		(0.090)	(0.065)	(0.090)	(0.064)
(5)Age when stopped education	16-19 years	0.1921***	0.1580***	0.1758***	0.1063***
		(0.037)	(0.033)	(0.037)	(0.032)
	20 years and older	0.2912***	0.3182***	0.2644***	0.2511***
		(0.045)	(0.036)	(0.045)	(0.036)
	Still Studying	0.0501	-0.1041*	0.0341	-0.1356**
		(0.085)	(0.062)	(0.084)	(0.060)
	No full-time education	-0.1002	-0.0432	-0.1061	-0.0305
		(0.112)	(0.106)	(0.111)	(0.103)
	Ref + DK	-0.1331	0.0891	-0.1659*	0.0936
		(0.090)	(0.086)	(0.089)	(0.084)
(6)Marital status	Living with partner	-0.0407	-0.0617*	-0.0434	-0.0548
		(0.049)	(0.034)	(0.049)	(0.033)
	Single	-0.1594***	-0.3166***	-0.1577***	-0.2894***
		(0.046)	(0.033)	(0.045)	(0.032)
	Divorced or separated	-0.0736	-0.2181***	-0.0715	-0.2082***
		(0.049)	(0.036)	(0.049)	(0.035)
	Widow	-0.1424***	-0.1803***	-0.1278***	-0.1345***
		(0.040)	(0.037)	(0.040)	(0.036)
	Ref + Other	-0.4887***	-0.3739***	-0.4639***	-0.3070***
		(0.137)	(0.113)	(0.136)	(0.110)
(7)Number of children	One	-0.0005	0.0925***	-0.0024	0.0894***
		(0.047)	(0.034)	(0.047)	(0.033)
	Two	0.0317	0.0722*	0.0187	0.0701*
		(0.057)	(0.039)	(0.057)	(0.039)
	Three	-0.0922	0.0442	-0.1239	0.0461
		(0.101)	(0.075)	(0.100)	(0.073)
	Four or more	-0.1855	-0.0662	-0.1905	-0.0503
		(0.129)	(0.102)	(0.129)	(0.099)
(8)Difficulties paying bills	From time to time	0.0734	0.1215***	0.0647	0.0981**
		(0.046)	(0.041)	(0.046)	(0.040)
	Almost never/never	0.2420***	0.2207***	0.2292***	0.1720***
		(0.046)	(0.040)	(0.046)	(0.039)
	Ref	0.2491**	-0.0358	0.2314**	-0.0765
		(0.116)	(0.086)	(0.114)	(0.084)
(9)Social class	Lower middle class	-0.0126	0.1327***	-0.0095	0.1180***
		(0.040)	(0.032)	(0.040)	(0.031)
	Middle class	-0.0414	0.1515***	-0.0439	0.1386***
		(0.033)	(0.025)	(0.033)	(0.025)
	Upper middle class	0.0195	0.1397***	0.0146	0.1313***
		(0.072)	(0.047)	(0.071)	(0.046)
	Higher class	-0.2278	0.0362	-0.2925	0.0451
		(0.183)	(0.131)	(0.180)	(0.129)
	Other+None+Ref+DK	0.0173	0.0330	0.0193	0.0264
		(0.063)	(0.052)	(0.062)	(0.051)
(10)Size of community	Small urban area	0.0341	0.0580**	0.0273	0.0499**
		(0.032)	(0.026)	(0.032)	(0.025)
	Large urban area	0.0526	0.0530**	0.0509	0.0396
		(0.032)	(0.025)	(0.032)	(0.024)
(11)Left-right political placement	Centre	-0.0296	0.0183	-0.0216	0.0175
		(0.035)	(0.026)	(0.034)	(0.026)
	Right	-0.0383	-0.0210	-0.0292	-0.0174
		(0.038)	(0.029)	(0.037)	(0.028)
	DK/Ref	0.0664	-0.0990***	0.0768*	-0.1045***
		(0.041)	(0.032)	(0.040)	(0.031)

Table 3: Estimates of the Probit and Heckman Sample Selection Models

Variable	Category	Probit		Heckman Country	
		Awareness	Influence	Awareness	Influence
(12)Political interest index	Medium	0.0046	-0.0679**	0.0013	-0.0662**
		(0.039)	(0.029)	(0.039)	(0.029)
	Low	-0.0106	-0.2037***	-0.0036	-0.1942***
		(0.047)	(0.035)	(0.047)	(0.034)
	Not at all	-0.2278***	-0.3321***	-0.2058***	-0.2844***
		(0.046)	(0.036)	(0.046)	(0.035)
(13)Facilitate energy choice	Tend to agree	-0.0967***	-0.1116***	-0.0956***	-0.0941***
		(0.028)	(0.021)	(0.027)	(0.021)
	Tend to disagree	-0.2121***	-0.1481***	-0.1915***	-0.1176***
		(0.055)	(0.042)	(0.055)	(0.041)
	Totally disagree	-0.1573	-0.3951***	-0.1617*	-0.3667***
		(0.099)	(0.068)	(0.098)	(0.067)
	DK	-0.1316**	-0.3537***	-0.1222**	-0.2952***
		(0.059)	(0.054)	(0.058)	(0.052)
(14)Energy-efficient products	Mentioned	0.0504*	0.1779***	0.0513*	0.1655***
		(0.030)	(0.023)	(0.030)	(0.022)
(15)Clear information	Mentioned	0.0224	0.0887***	0.0267	0.0810***
		(0.030)	(0.023)	(0.029)	(0.022)
(16)Energy Label - Responsibility	The European Union	0.3111***	0.1855***	0.3115***	0.1562***
		(0.049)	(0.037)	(0.049)	(0.036)
	The industry	0.2899***	0.0453	0.2889***	0.0130
		(0.060)	(0.044)	(0.060)	(0.043)
	Consumer org.	0.0825	0.0510	0.0762	0.0406
		(0.060)	(0.045)	(0.060)	(0.044)
	DK	-0.6595***	-0.3648***	-0.6586***	-0.2303***
		(0.048)	(0.040)	(0.048)	(0.041)
(17)Main information source	Newspapers/magazines	0.0260		0.0279	
		(0.047)		(0.047)	
	Radio	-0.0826		-0.0767	
		(0.059)		(0.057)	
	Internet websites	0.2917***		0.2909***	
		(0.045)		(0.044)	
	Online social networks	0.0976*		0.0835	
		(0.056)		(0.055)	
	Close ones	0.0149		-0.0121	
		(0.058)		(0.057)	
	Other + None + DK	-0.0171		-0.0505	
		(0.047)		(0.046)	
(18)Internet use	Often/sometimes	-0.0964**		-0.1128**	
		(0.045)		(0.044)	
	Never/no access	-0.4269***		-0.4852***	
		(0.040)		(0.040)	
	No access at all	-0.3470***		-0.4372***	
		(0.071)		(0.072)	
	Constant	1.3201***	0.6626***	1.3551***	0.7790***
		(0.135)	(0.084)	(0.133)	(0.101)
	Rho			-0.6414***	
				(0.066)	
	Country effects	yes	yes	yes	yes
	Observations	27,438	25,022	27,438	25,022

*** p<0.01, ** p<0.05, * p<0.1 - Standard errors in parentheses

In terms of marital status, all categories, except for those living with a partner, are less likely to recognize and be influenced by the label, with most coefficients being statistically significant when compared to married individuals.

The number of children in a household may also influence consumer behavior. Having one or two children significantly increases the likelihood of incorporating the label into purchasing decisions compared to the reference category of having no children. However, it is worth noting that the majority of survey respondents fall into the reference category, highlighting a substantial disparity between this group and other categories. Mills & Schleich (2010), which we reviewed in Section 2, also incorporate a variable capturing

the effect of the number of children —defined as those younger than six, whereas our specification considers children up to 14 years of age. Consistent with our results, their estimates across appliances show no significant association between the presence of children and knowledge of the appliance energy class—an aspect that can be interpreted as label awareness from a broader perspective.

Most survey respondents are individuals who rarely experience financial difficulties, and this group is significantly more likely to be aware of and influenced by the labels compared to those who frequently struggle with paying bills. Individuals who occasionally face financial difficulties are estimated to be significantly more likely to be influenced by the label in their purchasing decisions. However, this group does not exhibit a significant difference from the reference group in terms of their level of awareness.

Consistent with these findings, Mills & Schleich (2010) report that, for three out of five appliances analyzed, the likelihood of knowing the energy class of the appliance is influenced positively and significantly by the household income. On the other hand, household income significantly and positively influences the decision to purchase an efficiency-class A product only for washing machines.

The sample selection model reveals a strong positive relationship between self-identification as middle class and the likelihood of being influenced by the label when making purchasing decisions. However, the coefficients for the lower-middle and middle-class categories in the awareness model are negative and not statistically significant.

Individuals residing in small urban areas are significantly more likely to be influenced by the label compared to those living in rural areas. Furthermore, individuals living in large urban areas exhibit a significant positive effect for influence only in the model estimated with NUTS-region-level fixed effects, as shown in Table A.1 in the Appendix.

Individuals who in their political orientation are right- or center-leaning do not appear to differ significantly in their likelihood of being aware of or influenced by the labels compared to the reference group of left-leaning individuals across all models. Interestingly, individuals who either refuse to disclose their political position or are unsure are more likely to be aware of the labels but significantly less likely to be influenced by them. Additionally, individuals with medium, low, or no political interest are significantly less likely to be influenced by the labels, with the strongest negative effect observed among those with low or no interest. Moreover, individuals with no political interest are also significantly less likely to recognize the label.

When it comes to the question of whether it is the EU's responsibility to facilitate consumers' choice of energy sources and suppliers, individuals who do not *totally agree* are less likely to be aware of and influenced by the labels. Furthermore, respondents who associate energy policy with reducing energy consumption across the EU are more likely to be both aware of and influenced by the labels. Additionally, individuals who consider clear information as a priority for the EU's energy policy over the next decade are more likely to be influenced by the label.

The likelihood of being aware of and influenced by the label is higher for individuals who attribute responsibility for the label to the EU. In contrast, individuals who believe the industry is responsible are more likely to be aware of the label but do not show a significant increase in the likelihood of being influenced by it. Conversely, individuals who do not recognize the organization behind the label are significantly less likely to be both aware and influenced by the label in their purchasing decisions.

Finally, we include several variables related to information sources exclusively in our model of label awareness as explanatory variables. Our results indicate that digital media significantly increases the probability of an individual being aware of the label, while traditional media, such as television, appear to have no significant effect, despite TV being identified as the main source of information by most survey respondents. Internet use also influences label awareness, with reduced probabilities observed among individuals with limited or no internet access. The categories *never/no access* and *no access at all* strongly negatively affect label awareness across all models. This highlights that restricted internet access poses a substantial barrier to label awareness. However, it is worth noting that the number of individuals reporting no internet access in the dataset is relatively low.

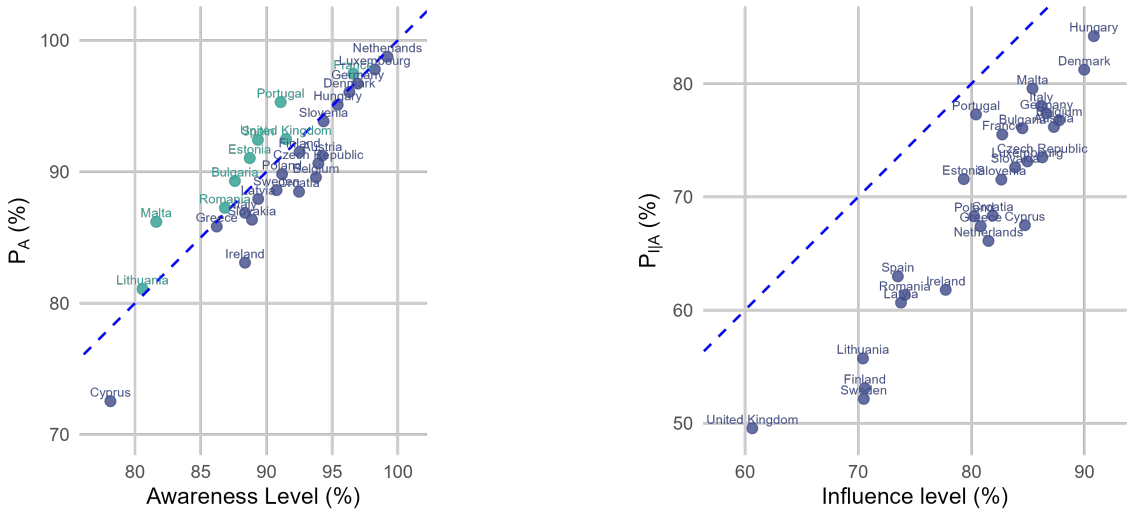
6.2 Model Predictions vs. Survey Responses

We use the estimated Heckman sample selection model with fixed effects at the country level to calculate the probabilities of awareness and influence attributable solely to geographic factors, keeping all other variables in the model at their base levels. Specifically, we estimate two types of probabilities: the probability of being aware of the label (P_A) and the conditional probability of being influenced by the label when making purchasing decisions, given awareness ($P_{I|A}$). Both these measures provide us with a country-specific estimate of awareness and influence levels.

In this subsection, we visually analyze the differences between the country-specific probabilities of awareness and influence and the observed levels derived from the raw survey data. The observed levels are presented in Figures 1 and 2. This exercise allows us identify the role played by socioeconomic and demographic variables in generating the geographic variation in awareness and influence levels.

Figure 4 compares P_A with the awareness level, and $P_{I|A}$ with the influence level. Figure 4a shows that most observations are on or near the 45-degree line, suggesting that country-specific factors are the primary drivers of geographic differences in label awareness. This implies that differences in the socio-economic characteristics of individuals across countries in the dataset do not significantly explain the variation in the fraction of individuals reporting label awareness.

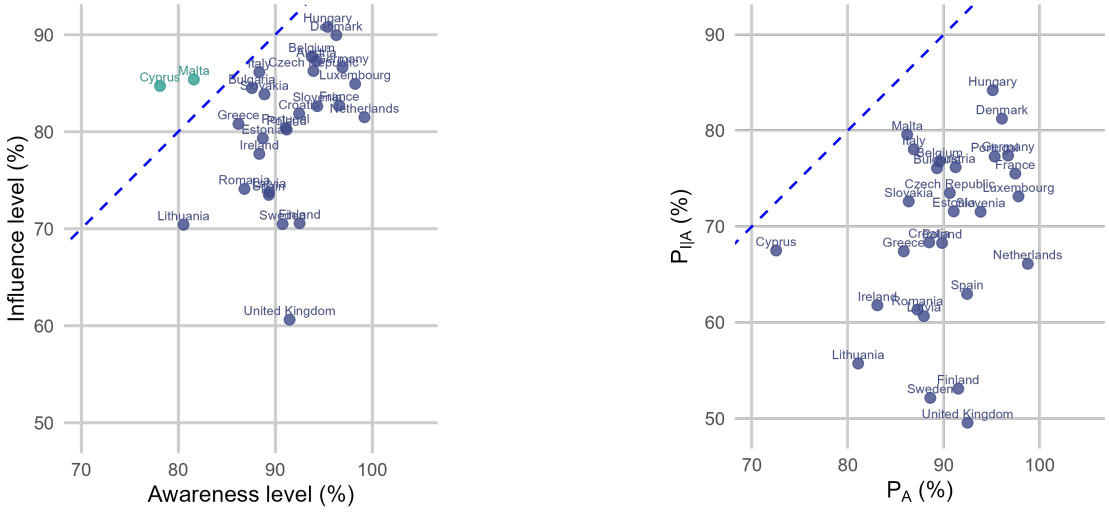
Figure 4: Comparing Adjusted Probabilities with Levels of Awareness and Influence



(a) (b)

In contrast, Figure 4b reveals that all observations fall below the 45-degree line, while still displaying substantial variation across countries. This indicates that individual characteristics are crucial in explaining label influence within each country. However, heterogeneity across countries persists due to additional country-specific factors.

Figure 5: Comparing Label Influence vs. Awareness: Probabilities and Percentages



(a) (b)

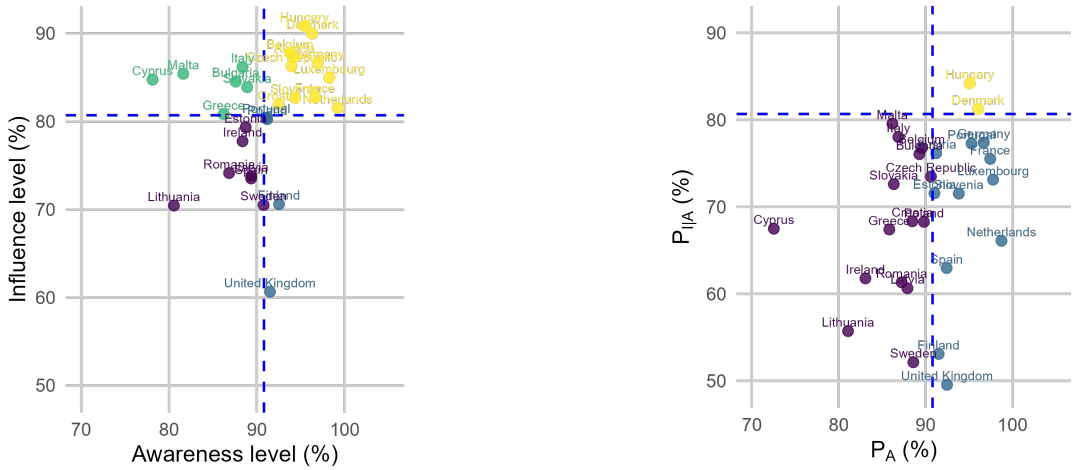
In Figure 5, we provide a comparative analysis of label awareness and influence by plotting the level of influence against the awareness level. In Figure 5a, both these measures are derived from the raw survey data, while in Figure 5b, we plot the estimated country specific conditional probability of awareness against the probability of awareness. Figure 5a shows that only in Cyprus and Malta does the influence level exceeds the awareness level. In all other countries, a higher fraction of people recognize the label than are

influenced by it when making purchase decisions.

After controlling for individual characteristics, Figure 5b shows that the probability of influence is more widely dispersed, ranging from 49.6% to 84.2% on the vertical axis, with all countries moving downward below the 45-degree line. This again highlights the role of individual characteristics in determining label influence, as opposed to label awareness. Moreover, as discussed in subsection 4.2, at the NUTS level, areas with a high influence levels are dispersed across Europe, whereas areas with a low influence levels are more concentrated in a few countries.

The quadrant-based comparison shown in Figure 6 provides a more detailed analysis of the impact of individual characteristics by country, using the average influence and awareness levels in the EU as reference lines. This figure presents the awareness-influence positioning of countries under two scenarios: Figure 6a is based on awareness and influence levels calculated from the raw survey data, and hence include the effects of individual characteristics, while Figure 6b shows the country-specific probabilities we derive using the estimates of the sample selection model, representing a hypothetical individual with baseline characteristics across all countries.

Figure 6: Quadrant-Based Comparison of Label Influence vs Awareness



(a) (b)

The measures based on the survey data place the countries across all four quadrants, with the majority—eleven countries—concentrated in Quadrant 1, characterized by high awareness and high influence. The remaining quadrants contain six, seven, and four countries, respectively. However, when examining country positions using the probabilities estimated from the sample selection model, significant shifts are observed. Notably, only Hungary and Denmark remain in Quadrant 1, suggesting that awareness and influence are less dependent on individual factors in these countries. In contrast, Belgium, Croatia, and the Czech Republic, initially located in this quadrant, moved to Quadrant 3, indicating that individual characteristics significantly affect both label awareness and influence

in these nations. The remaining countries that were initially in Quadrant 1 (Austria, France, Germany, Luxembourg, the Netherlands, and Slovenia) shifted to Quadrant 4, demonstrating that while individual factors strongly affect the influence of the label on purchasing decisions, they play a lesser role in shaping awareness.

Quadrant 2 in Figure 6b is notably empty. Recall that this figure is based on country-specific probabilities estimated from our model. All six countries originally in this quadrant—Bulgaria, Cyprus, Greece, Italy, Malta, and Slovakia—move to Quadrant 3, suggesting that individual characteristics predominantly shape influence levels without significantly altering the awareness of individuals in these countries. Based on the estimated probabilities, most countries (fifteen in total) are placed in Quadrant 3, indicating both low awareness and low influence of labels.

Ireland, Latvia, Lithuania, Romania, and Sweden remain in Quadrant 3 in Figure 6b, indicating that country-specific factors, rather than individual characteristics, drive both awareness and influence to lower levels in these countries. Poland is the only country that shifts from Quadrant 4 to Quadrant 3, suggesting that individual factors affect awareness without significantly affecting the label's influence. Conversely, Estonia and Spain move from Quadrant 3 to Quadrant 4, suggesting that individual factors negatively affect awareness without significantly impacting the label's influence. Finally, Finland, Portugal, and the United Kingdom remain in Quadrant 4, indicating that individual characteristics have a limited effect within these national contexts on both awareness of and influence by the labels.

7. Improving adoption of energy-efficient appliances through informational campaigns

In this subsection, we perform three counterfactual exercises by simulating an advertising campaign aimed at increasing awareness of individuals about the energy labels within specific population groups. We then analyze the impact of this increased awareness on the influence of the energy labels on consumption decisions. Unlike the previous section, these simulations compute unadjusted influence probabilities based on the characteristics and responses of each individual.

In the first scenario, we emulate an untargeted advertising campaign that aims to reach the entire population, ensuring that all respondents become aware of the label. This scenario corresponds to the broadest and most costly campaign, as it does not involve targeting specific groups.

The second counterfactual exercise focuses on a targeted advertising campaign designed to reach individuals who are least likely to be aware of the labels. This approach aims to optimize the campaign's impact by focusing on segments of the population where awareness levels are initially low.

In the third scenario, the campaign targets individuals who, although initially un-

aware of the labels, share characteristics with those who are highly influenced by the labels when they are aware. This approach seeks to maximize the influence of the labels on consumption decisions by reaching individuals most likely to respond positively to increased awareness.

In all three scenarios, awareness is artificially increased by raising the probability of awareness to 99% for the targeted group[5]. Following this adjustment, we compute the conditional probability of being influenced given awareness of the label, $P_{I|A}$, and the unconditional probability of being influenced, P_I, using the estimates from the Heckman sample selection model presented in Table 3 with country level fixed effects.

□ **Universal awareness campaign:** In Table 4, we present the probabilities of label awareness (P_A), the probability of being influenced conditional on awareness ($P_{I|A}$), and the unconditional probability of being influenced (P_I) in columns two to four, as calculated from the raw survey data. The subsequent three columns display the same probabilities following an intervention that raises awareness to 99% across the entire population. Finally, the last three columns of the table illustrate the changes in these probability measures induced by the intervention.

Table 4: Probabilities Before and After Raising Awareness Across the Entire Population

Country	**Pre-targeting**			**Post-targeting**			**Absolute Difference**		
	P_A	$P_{I\|A}$	P_I	P_A	$P_{I\|A}$	P_I	P_A	$P_{I\|A}$	P_I
Austria	94.27	86.6	82.15	99	87.62	86.74	4.73	1.02	4.59
Belgium	93.52	87.31	82.32	99	88.49	87.6	5.48	1.18	5.28
Bulgaria	87.42	82.14	73.55	99	85.27	84.42	11.58	3.13	10.87
Croatia	92.49	80.62	75.72	99	82.5	81.68	6.51	1.88	5.96
Cyprus	78.38	79.58	66.29	99	85.48	84.63	20.62	5.9	18.34
Czech Republic	94.24	85.43	81.1	99	86.55	85.68	4.76	1.12	4.58
Denmark	96.19	89.48	86.55	99	90.16	89.26	2.81	0.68	2.71
Estonia	88.79	77.36	70.85	99	80.71	79.9	10.21	3.35	9.05
Finland	92.91	68.54	65.2	99	70.88	70.17	6.09	2.34	4.97
France	96.56	82.34	80.03	99	83.15	82.32	2.44	0.81	2.29
Germany	96.73	86.36	83.88	99	86.95	86.08	2.27	0.59	2.2
Greece	86.23	77.37	69.41	99	81.49	80.68	12.77	4.12	11.27
Hungary	94.97	90.53	86.58	99	91.39	90.48	4.03	0.86	3.9
Ireland	88.2	75.24	68.33	99	78.7	77.91	10.8	3.46	9.58
Italy	88.4	84.04	76.21	99	86.85	85.98	10.6	2.81	9.77
Latvia	89.53	71.57	65.92	99	74.94	74.19	9.47	3.37	8.27
Lithuania	80.38	66.04	57.03	99	72.77	72.04	18.62	6.73	15.01
Luxembourg	98.18	84.63	83.37	99	84.97	84.12	0.82	0.34	0.75
Malta	81.96	81.56	69.48	99	86.17	85.3	17.04	4.61	15.82
Netherlands	99.18	81.5	80.92	99	81.55	80.73	-0.18	0.05	-0.19
Poland	90.42	78.85	72.88	99	81.5	80.68	8.58	2.65	7.8
Portugal	90.39	78.86	73.12	99	81.74	80.93	8.61	2.88	7.81
Romania	86.81	72.09	64.5	99	76.09	75.33	12.19	4	10.83
Slovakia	88.73	82.45	74.63	99	85.11	84.26	10.27	2.66	9.63
Slovenia	94.23	81.57	77.76	99	83.01	82.18	4.77	1.44	4.42
Spain	89.88	70.44	65.62	99	73.95	73.21	9.12	3.51	7.59
Sweden	91.16	69.34	64.42	99	72.15	71.43	7.84	2.81	7.01
United Kingdom	91.59	58.65	55.42	99	61.73	61.11	7.41	3.08	5.69

For Pre- and Post-Targeting columns:P_A = average probability of awareness; $P_{I|A}$ = average conditional probability of influence given awareness; P_I = average unconditional probability of influence. All values are percentages.
For absolute differences columns, values represent changes in percentage points.

Given that $P_{I|A}$ is defined as P_I/P_A, the conditional probability of being influenced equals the unconditional probability when P_A reaches 100%. Thus, in this scenario,

[5]We set the probability of awareness at 99%, rather than 100%, to avoid numerical issues in the subsequent estimation of both conditional and unconditional probabilities of being influenced.

where the campaign aims to increase awareness (P_A) to 99%, $P_{I|A}$ and P_I become very similar. This counterfactual exercise provides an upper limit on the potential impact of an awareness-increasing campaign on label influence in consumption choices across countries.

For instance, in Austria, the post-campaign conditional probability of being influenced, given label awareness, is 87.62%, while the unconditional probability is 86.74%. The close proximity of these values suggests that the maximum achievable influence under near-universal awareness is around 87%. This information highlights the effectiveness ceiling for label influence, even with extensive awareness campaigns, and offers valuable insights for policymakers aiming to enhance label influence through increased awareness. However, as we noted above, since this campaign targets the entire population, it is expected to require more resources due to potentially higher implementation costs.

Overall, the post-targeting change in P_I is closely tied to the extent of pre-targeting variation in P_A. Countries where targeting led to significant increases in P_A—such as Cyprus, Lithuania, and Malta—experience the highest positive impact on the unconditional probability of influence, P_I. Greece, Bulgaria, and Romania also see notable increases in P_A, exceeding 10 percentage points, which are similarly reflected in their estimated unconditional probability of influence. Conversely, countries with the highest initial awareness——such as Denmark, France, Germany, Luxembourg, and the Netherlands–—exhibit the smallest changes in both P_A and P_I.[6]

□ **Targeting individuals with a low probability of awareness:** This approach targets countries with awareness rates below 90%, as these present the greatest potential for improvement. Figure 7 displays a heatmap based on the average probability of awareness calculated from the model using individual characteristics. This heatmap helps us identify the demographic groups with the lowest likelihood of being aware of the label. The demographic factors associated with lower awareness vary by country, suggesting that such campaigns must be tailored to each country's unique context. However, common factors linked to low label awareness include older age, lack of full-time education, and education ending at or before age 15.

Table 5 presents a detailed breakdown of the relevant demographics for countries with an awareness probability below 90%. However, all demographic groups in Estonia, Ireland, Malta, and Spain exhibit quite high average probability of awareness exceeding 80%. Consequently, these countries are not included in the analysis.

We artificially adjusted the probability of awareness to 99% for all individuals exhibiting at least one of the relevant demographic characteristics identified for each country to emulate such a targeted advertising campaign. Table 6 presents the pre- and post-intervention probability measures for awareness and influence, as well as the changes induced by the simulated intervention. Additionally, the table includes three columns summarizing the size of the targeted group: the first two show the number of individuals aware of these characteristics both before and after the intervention, while the last

[6]In the Netherlands, these variations are negative, as the country reports an average awareness level slightly exceeding 99% in the pre-campaign phase.

column displays the proportion of these individuals within the full sample during the post-targeting phase.

Figure 7: Probability of Awareness by Characteristic

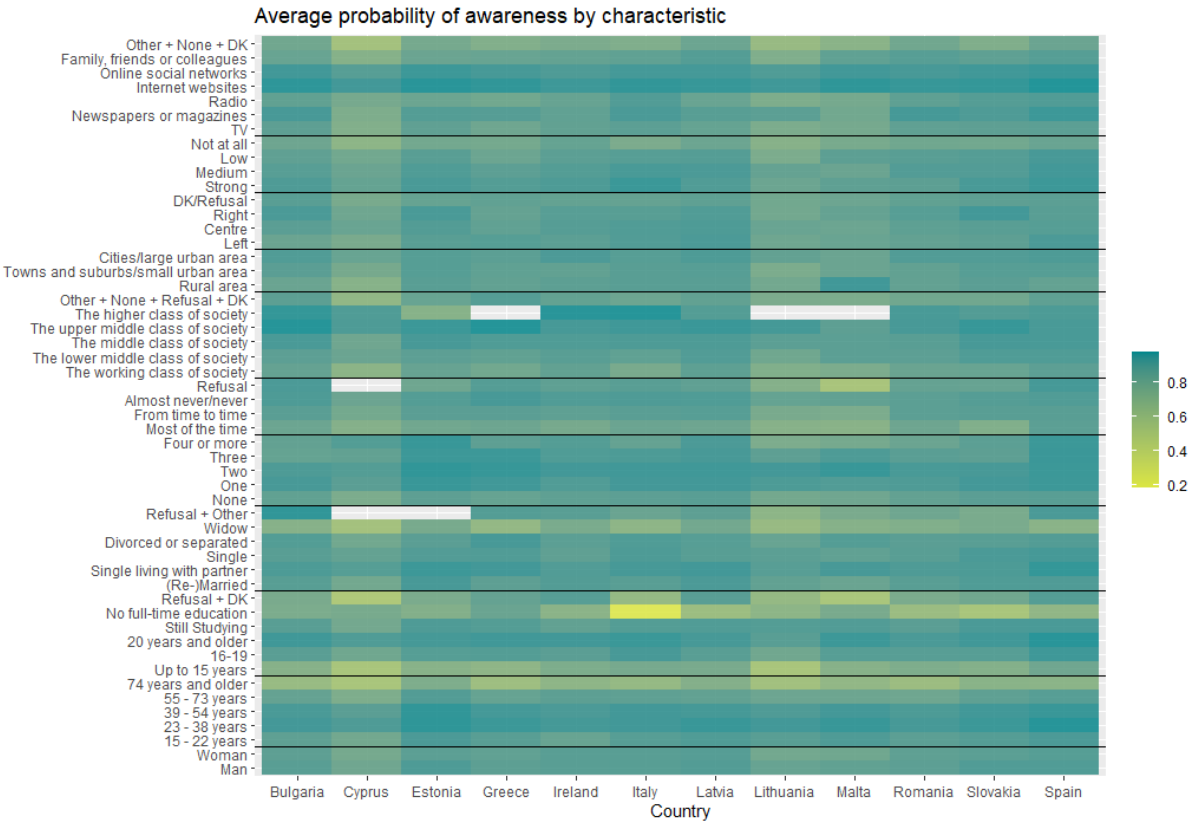


Table 5: Individual Characteristics with the Lowest Awareness Probability by Country

Bulgaria	**Cyprus**	**Greece**	**Italy**	**Latvia**	**Lithuania**	**Romania**	**Slovakia**
74 years and older	74 years and older Education up to 15 years Widow	74 years and older	No full-time education	No full-time education	74 years and older Education up to 15 years	74 years and older No full-time education	No full-time education

This intervention proves particularly effective for countries like Cyprus and Lithuania, where the proportion of the targeted group within the sample is relatively large. Conversely, targeting individuals less likely to be aware of the labels is less impactful in countries such as Italy, Latvia, and Slovakia, where the size of the target group is comparatively smaller.

Table 6: Probabilities Before and After Raising Awareness for Individuals Less Likely to Be Aware

Country	Pre-targeting			Post-targeting			Absolute Difference			Individuals aware		
	P_A (%)	$P_{I\|A}$ (%)	P_I (%)	P_A (%)	$P_{I\|A}$ (%)	P_I (%)	P_A	$P_{I\|A}$	P_I	Before	After	Sample Share
Bulgaria	87.42	82.14	73.55	89.78	82.98	75.61	2.36	0.84	2.06	37	62	6.0
Cyprus	78.38	79.58	66.29	90.20	83.69	76.15	11.82	4.11	9.86	72	140	27.8
Greece	86.23	77.37	69.41	91.11	79.25	73.33	4.88	1.88	3.92	66	119	11.7
Italy	88.40	84.04	76.21	88.48	84.07	76.25	0.08	0.03	0.04	0	1	0.1
Latvia	89.53	71.57	65.92	89.58	71.59	65.95	0.05	0.02	0.03	1	1	0.1
Lithuania	80.38	66.04	57.03	89.51	69.64	63.60	9.13	3.60	6.57	126	214	21.3
Romania	86.81	72.09	64.50	88.73	72.84	65.89	1.92	0.75	1.39	34	50	4.8
Slovakia	88.73	82.45	74.63	88.87	82.50	74.74	0.14	0.05	0.11	1	3	0.28

For Pre- and Post-Targeting columns:P_A = average probability of awareness; $P_{I|A}$ = average conditional probability of influence given awareness; P_I = average unconditional probability of influence.
For absolute differences columns, values represent changes in percentage points.

☐ **Targeting individuals who are initially unaware but share characteristics with those who are highly influenced:** Similar to the previous exercise, we focus on countries with awareness probability below 90%. The characteristics used for targeting are identified by filtering individuals whose P_I values exceed 80%—indicating high influence—and calculating the average probability of influence by characteristic within this group. Figure 8 visualizes the performance of average P_I values by characteristic, while Table 7 lists the characteristics with the highest P_I values by country. This approach incorporates categories from at least three variables for targeting in each country.

Figure 8: Unconditional Probability of Being Influenced by Characteristic

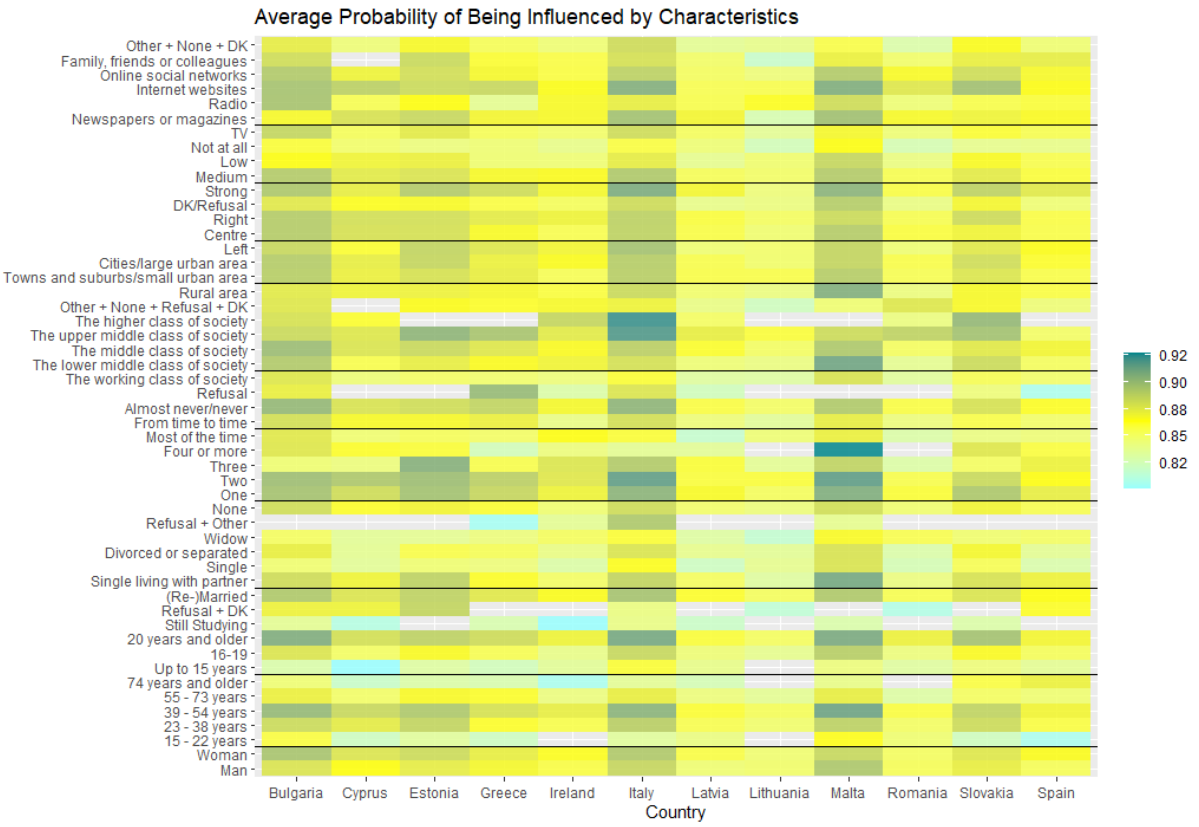


Table 7: Individual Characteristics with the Highest Unconditional Probability of Being Influenced by Country

Bulgaria	**Cyprus**	**Estonia**	**Greece**	**Ireland**	**Italy**
Education up to 20 years and older	Two children	Three children	The upper middle class of society	The higher class of society	The higher class of society
Almost never-/never Difficulties paying bills	Main information source: Internet websites	The upper middle class of society	Two children	Three children	The upper middle class of society
39 - 54 years	39 - 54 years	Two children	Almost never-/never Difficulties paying bills	Two children	Two children
		One child		The upper middle class of society	Education up to 20 years and older
		39 - 54 years		39 - 54 years	

Latvia	**Lithuania**	**Malta**	**Romania**	**Slovakia**	**Spain**
The upper middle class of society	Main information source: Radio	Four or more children	The upper middle class of society	The higher class of society	Strong political interest
Main information source: Newspapers or magazines	Two children	Two children	Main information source: Internet websites	Main information source: Internet websites	Main information source: Family, friends or colleagues
Strong political interest	The upper middle class of society	39 - 54 years	Education up to 20 years and older	The upper middle class of society	One child
		The lower middle class of society		Education up to 20 years and older	

Table 8 presents the probabilities of awareness and influence before and after targeting. This scenario proves more effective than the previous one, resulting in a higher increase in the influence probability, P_I, across all considered countries except Cyprus, Greece, and Lithuania. The impact varies across countries, depending on the share of aware individuals with identified characteristics and, consequently, how many new individuals are targeted by this information campaign. For example, there are only eight individuals in Estonia who are unaware but likely to be influenced, whereas in Bulgaria, this group includes fifty-two individuals. As a result, the highest impact on P_I is observed in Bulgaria.

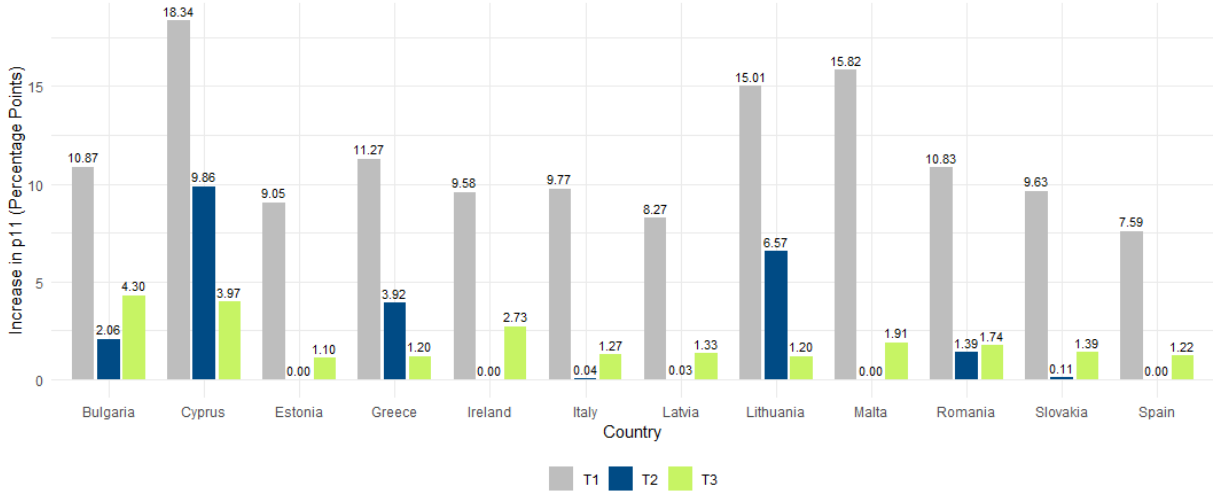
Table 8: Probabilities Before And After Raising Awareness for Individuals Who are Initially Unaware but Share Characteristics With Those Who are Highly Influenced

Country	**Pre-targeting**			**Post-targeting**			**Absolute Difference**			**Individuals aware**		
	P_A (%)	$P_{I\|A}$ (%)	P_I (%)	P_A (%)	$P_{I\|A}$ (%)	P_I (%)	P_A	$P_{I\|A}$	P_I	**Before**	**After**	**Sample Share**
Bulgaria	87.42	82.14	73.55	91.88	83.15	77.85	4.46	1.01	4.3	548	600	58.1
Cyprus	78.38	79.58	66.29	82.46	80.32	70.26	4.08	0.74	3.97	188	211	41.9
Estonia	88.79	77.36	70.85	89.93	77.63	71.95	1.14	0.27	1.1	341	349	34.8
Greece	86.23	77.37	69.41	87.49	77.67	70.61	1.26	0.3	1.2	224	244	24.0
Ireland	88.2	75.24	68.33	91.13	76.03	71.06	2.93	0.79	2.73	384	419	41.6
Italy	88.4	84.04	76.21	89.7	84.25	77.48	1.3	0.21	1.27	281	296	28.9
Latvia	89.53	71.57	65.92	90.98	72.04	67.25	1.45	0.47	1.33	174	189	18.8
Lithuania	80.38	66.04	57.03	81.8	66.52	58.23	1.42	0.48	1.2	92	108	10.8
Malta	81.96	81.56	69.48	83.99	82.03	71.39	2.03	0.47	1.91	123	133	26.9
Romania	86.81	72.09	64.5	88.63	72.59	66.24	1.82	0.5	1.74	248	278	26.7
Slovakia	88.73	82.45	74.63	90.15	82.73	76.02	1.42	0.28	1.39	342	353	32.6
Spain	89.88	70.44	65.62	91.23	70.91	66.84	1.35	0.47	1.22	269	283	28.2

For Pre- and Post-Targeting columns: P_A = average probability of awareness; $P_{I|A}$ = average conditional probability of influence given awareness; P_I = average unconditional probability of influence.
For absolute differences columns, values represent changes in percentage points.

Figure 9 illustrates the changes in label influence resulting from our simulations under the counterfactual scenarios for targeted advertising campaigns. This figure makes it possible for us to compare the effectiveness of each targeting exercise in increasing label influence on consumption decisions. As expected, a non-targeted campaign aiming to reach everyone (T1) produces the largest improvements in predicted changes in label influence. However, as previously noted, this approach would also be the most expensive to implement.

Figure 9: Comparative Contributions of Targeting Actions to Unconditional Probability of Influence by Country



T1: Perfect targeting, T2: Targeting individuals less likely to be aware, T3: Targeting individuals who are highly susceptible to influence but initially unaware. A value of 0.0 in T2 indicates countries excluded from the targeting exercise due to average awareness probabilities exceeding 80% across all demographic groups

The other two campaigns (T2 and T3) involve targeting a limited group of individuals based on their demographic characteristics, making them less costly than a universal campaign. However, their effectiveness in improving label influence on purchase decisions is also considerably lower. As can be seen in Figure 9, in some countries the campaign T2 performs better than campaign T3, while in others the performance of T3 is better. When we compare the best performing campaign (T2 or T3) to the ideal scenario when no targeting takes place, namely campaign T1, we observe that the targeted campaigns can in some cases reach about 35% to 54% of the ideal campaign's performance. For instance, in Bulgaria, T3 emerges as the most effective strategy, contributing 40.68% of the maximum potential increase observed in T1. Nevertheless, even with these targeted improvements, the influence probability (P_I) in these countries remains below 78%, with Lithuania showing the lowest level at 63.6%.

In countries where a significant portion of the population is unaware of the labels, targeting campaigns aimed at individuals less likely to be aware yields substantial improvements in label influence. However, in countries with a moderate share of unaware individuals, focusing on those most likely to be influenced proves to be a better strategy.

A comprehensive evaluation of different campaigns must account for the associated costs, which we leave for future research.

8. Conclusions

We use a Eurobarometer survey of 27,438 individuals across 28 EU Member States commissioned by the European Commission in 2019 to analyze respondents' awareness of the EU Energy Labeling scheme and the impact of labels on the purchases of electrical appliances. Our empirical results offer insights into consumer behavior, which may provide not only important guidance for EU energy policy design concerning energy labeling but also prove useful in designing campaigns to increase the influence of such labels on purchase decisions.

Based on the estimated determinants, we identified demographic factors that could be considered in future initiatives designed to enhance label awareness and its influence on purchasing decisions. Gender plays a fundamental role, as women are more likely to be aware of and act on labels, suggesting that policy initiatives could benefit from gender-specific communication strategies to address the gap in label awareness and its influence among men. Age and education also emerge as significant factors. Middle-aged individuals and those with more years of education are more likely to be influenced, whereas older adults and students tend to be less influenced. Targeted outreach efforts addressing the specific concerns of these groups—such as the complexity of energy-efficient products or financial constraints—could help overcome these barriers. Educational campaigns, particularly in schools and universities, could promote long-term behavioral change among students.

Financial stability also significantly affects label influence, pointing to the potential role economic incentives—such as subsidies or rebates for energy-efficient products—can play in boosting label influence among those with tighter budgets. Social class and political interest are also important considerations for future policy frameworks. Middle-class individuals are more likely to be influenced by the label, while those with low political interest are less likely to recognize or act on them. Additionally, digital information channels could serve as a more effective platform for promoting labels than traditional media, and rural and underserved areas could represent opportunities to enhance the impact of labels.

The strong positive correlation between recognizing the EU as the institution responsible for labeling and both label awareness and influence underscores the importance of maintaining public confidence in the EU. Clear provision of energy policy information, as well as campaigns aimed at improving the adoption of energy-efficient devices, should contribute to keeping public trust at a high level.

Geographic variations in energy label awareness and influence across Europe have important implications for policy interventions. We conduct three exercises in which we

assume that a policymaker can increase label awareness among all unaware individuals or target those with specific characteristics. Using our model, we compute changes in average influence resulting from these interventions. The effects of targeting vary across countries depending on the size of the group targeted by the information campaign. These exercises can serve as a basis for cost-benefit analyses of informational targeting. We should, however, note that a high level of awareness is not a guarantee that labels will considerably influence purchasing decisions. Thus, awareness alone is insufficient to drive behavioral change. Policies that extend beyond merely providing information—such as stricter regulations on energy efficiency standards or more visible consumer incentives—may be necessary.

The estimated probabilities for awareness, after controlling for individual characteristics, align closely with country-level awareness shares derived from survey data. However, the estimated probabilities for influence show a larger variation than the survey data shares. This suggests that individual characteristics have a stronger impact on the degree to which labels affect purchases than they affect awareness. Despite this, substantial heterogeneity remains across countries.

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Appendix A

Table A.1: Estimates of the Heckman Sample Selection Models (NUTS Fixed Effects)

Variable	**Category**	**Awareness**	**Influence**
(3)Gender	Woman	0.0412	0.1001***
		(0.026)	(0.020)
(4)Age	23 - 38 years	0.1894**	0.1247**
		(0.075)	(0.052)
	39 - 54 years	0.1710**	0.2445***
		(0.080)	(0.055)
	55 - 73 years	0.0239	0.0706
		(0.083)	(0.057)
	74 years and older	-0.3035***	-0.0951
		(0.090)	(0.065)
(5)Age when stooped education	16-19 years	0.1759***	0.1074***
		(0.037)	(0.032)
	20 years and older	0.2635***	0.2573***
		(0.046)	(0.036)
	Still Studying	0.0312	-0.1267**
		(0.085)	(0.061)
	No full-time education	-0.0363	-0.0036
		(0.113)	(0.104)
	Ref + DK	-0.1038	0.0952
		(0.093)	(0.085)
(6)Marital status	Living with partner	-0.0444	-0.0535
		(0.050)	(0.034)
	Single	-0.1550***	-0.2808***
		(0.046)	(0.033)
	Divorced or separated	-0.0889*	-0.2113***
		(0.049)	(0.036)
	Widow	-0.1329***	-0.1294***
		(0.040)	(0.036)
	Ref + Other	-0.4166***	-0.3363***
		(0.141)	(0.111)
(7)Number of children	One	-0.0022	0.0936***
		(0.047)	(0.034)
	Two	0.0421	0.0692*
		(0.058)	(0.039)
	Three	-0.0826	0.0605
		(0.102)	(0.074)
	Four or more	-0.1865	-0.0341
		(0.130)	(0.100)
(8)Difficulties paying bills	From time to time	0.0644	0.0988**
		(0.047)	(0.040)
	Almost never/never	0.2265***	0.1726***
		(0.047)	(0.040)
	Ref	0.1891	-0.0646
		(0.116)	(0.085)
(9)Social class	Lower middle class	-0.0018	0.1264***
		(0.040)	(0.031)
	Middle class	-0.0380	0.1390***
		(0.033)	(0.025)
	Upper middle class	0.0232	0.1363***
		(0.072)	(0.046)
	Higher class	-0.2852	0.0546
		(0.182)	(0.130)
	Other+None+Ref+DK	0.0380	0.0321
		(0.063)	(0.051)
(10)Size of community	Small urban area	0.0271	0.0500**
		(0.033)	(0.026)
	Large urban area	0.0678**	0.0455*
		(0.033)	(0.025)

*** p<0.01, ** p<0.05, * p<0.1 - Standard errors in parentheses

Table A.1: Estimates of the Heckman Sample Selection Models (NUTS Fixed Effects)

Variable	**Category**	**Awareness**	**Influence**
(11)Left-right political placement	Centre	-0.0193	0.0128
		(0.035)	(0.026)
	Right	-0.0252	-0.0201
		(0.038)	(0.028)
	DK/Ref	0.0723*	-0.0974***
		(0.041)	(0.031)
(12)Political interest index	Medium	-0.0016	-0.0700**
		(0.040)	(0.029)
	Low	-0.0077	-0.2058***
		(0.047)	(0.035)
	Not at all	-0.2104***	-0.2920***
		(0.046)	(0.035)
(13)Facilitate energy choice	Tend to agree	-0.0925***	-0.0911***
		(0.028)	(0.021)
	Tend to disagree	-0.1784***	-0.1025**
		(0.056)	(0.042)
	Totally disagree	-0.1582	-0.3553***
		(0.099)	(0.068)
	DK	-0.1065*	-0.2936***
		(0.059)	(0.053)
(14)Energy-efficient products	Mentioned	0.0496*	0.1668***
		(0.030)	(0.022)
(15)Clear information	Mentioned	0.0339	0.0853***
		(0.030)	(0.022)
(16)Energy Label - Responsibility	The European Union	0.3106***	0.1529***
		(0.049)	(0.036)
	The industry	0.2987***	0.0093
		(0.061)	(0.044)
	Consumer org.	0.0842	0.0393
		(0.061)	(0.044)
	DK	-0.6628***	-0.2416***
		(0.049)	(0.041)
(17)Main information source	Newspapers/magazines	0.0283	
		(0.047)	
	Radio	-0.0579	
		(0.058)	
	Internet websites	0.2906***	
		(0.045)	
	Online social networks	0.0797	
		(0.055)	
	Close ones	-0.0130	
		(0.058)	
	Other + None + DK	-0.0702	
		(0.047)	
(18)Internet use	Often/sometimes	-0.1139**	
		(0.044)	
	Never/no access	-0.4925***	
		(0.039)	
	No access at all	-0.4207***	
		(0.070)	
	Constant	1.2418***	0.7880***
		(0.105)	(0.084)
	Observations	27,438	27,438

*** p<0.01, ** p<0.05, * p<0.1 - Standard errors in parentheses