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The impact of socioeconomic and behavioural factors for purchasing energy efficient household appliances: A case study for Denmark

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Abstract

Increasing the share of evermore energy efficient household electric appliances is one strategy to address environmental impacts arising from residential electricity demand. Hence, governments and energy actors are interested in the determining factors behind the consumer choice of conventional versus high efficiency labelled appliances. This study employs empirical survey data from the Danish Energy Agency to model influential factors behind Danish consumer choice of energy efficient appliances. To estimate consumer propensities, we use a logistic regression model over a set of socioeconomic, demographic, and behavioural variables. The study regresses over this unique combination of end-use behavioural variables by creating an energy efficiency index. Statistical results show that housing type, quantity of inhabitants, age, and end-use behaviour are strong predictors for choosing energy efficient appliances. Interestingly, income is a weaker predictor. Despite a relatively wealthy national income and well-educated population, information campaigns have been largely ineffective in driving high efficiency investments. In light of this study's results and exogenous factors such as urbanising demographics and shifting Danish housing stock towards apartments, the study suggests improved information campaigns by targeting key demographics.

Keywords: Consumer behaviour; energy efficiency; household appliances; purchase propensity; regression model

1. Introduction

Like other Western European nations, Danish household electricity consumption accounts for more than 20% of total electricity demand ([Gaspar and Antunes 2011](#)). Electric devices such as dishwashers, washing machines, cooking hobs, microwaves, fridges and freezers account for 50% of this figure ([FEHA 2017](#)). The quantity of household appliances, due to rising wealth and access to technology, has increased dramatically over the last decades according to the Danish Association for Suppliers of Electrical Domestic

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Appliances (FEHA).

In 1992, the European Union (EU) addressed rising household electricity demand and its environmental impacts with the EU Directive 92/75/EC establishing the energy consumption labelling scheme for most white goods and light bulbs (EU 1992). Its aim was to increase consumer awareness of energy consumption by demanding clearly visible labels classifying electric devices from the most energy efficient (Class A) to the least (Class G). Since 1995, EU consumers have been exposed to this letter-grade labelling system. Given increasing appliance energy efficiency, the EU extended the labelling system with Directive 2010/30/EU by introducing classes A+, A++ and A+++, and is planning to rescale the metric to the A-G scale in the future (see EU 2015 and EU 2017 for details).

In light of EU energy saving efforts, the purchasing propensity for EE (energy efficient) appliances, coupled with efficient end-use, now carry greater importance. The drivers of appliance purchasing are diverse: short and long run household economics, attitudes towards the environment, and casual choice, among others. By addressing these factors, governments may improve efficiency standards and labelling campaigns. Due to their diverse nature, though, leveraging these factors and estimating their effect on appliance purchasing might be challenging. Data from surveys assessing consumer preferences could represent an initial valuable source of information while tools like consumer choice models, for instance, could help drawing considerations about purchasing choices.

Our study is motivated by the following research questions. Which socioeconomic characteristics best predict the consumer selection of high-labelled household appliances? What impact has the end-user behaviour, in relation to energy use and savings, on purchasing such household appliances? Which energy end-use daily actions are more relevant for predicting the purchase of appliances? Accordingly, which policies can increase consumer consciousness of energy efficiency so as to adopt high-labelled household appliances thus reducing CO₂ emissions?

To address these research questions, we considered the results of a Danish Energy Agency (DEA) survey over a representative housing sample, and developed a logistic regression model to predict the propensity of the Danish consumer to choose a new, highest-labelled household appliance. In this model, we employed socioeconomic and demographic variables (e.g., income age, income and job of the consumer, housing type, size, year built, and number of inhabitants) as well as a behavioural energy efficiency variable (EE-index) calculated from a set of consumer energy end-use behavioural questions (e.g., turning off the power sockets during the night and adapting the heating system to the seasons). Based on the model results, we estimated propensities of Danish consumers to choose more efficient appliances at the moment of purchase. Eventually, we drew policy recommendations, relevant beyond the Danish context, to foster energy efficient behaviours and increase the purchase of EE appliances in the residential sector.

This paper contributes to the field by developing novel methodology resulting in practical findings that can be useful for policy makers and governmental institutions. On the methodological side, the

contributions of the paper consist of (i) the construction of the EE-index that gathers and synthesizes a rich set of consumer behavioural characteristics and daily actions regarding energy end-use and energy savings, and (ii) the integration of such index in a consumer choice model to study the joint effect of socioeconomic, demographic, and behavioural variables on consumers energy efficiency investment choices. Finally, unlike previous studies, (iii) we performed an extensive investigation of a behavioural index through correlation matrices and by examining interrelations between its constituent parts.

On the practical side, we find from our statistical results that socioeconomic and behavioural characteristics are highly significant when explaining the choice of purchasing EE appliances. Specifically, income, housing type, quantity of inhabitants, age, and end-use behaviour are predictors for choosing energy efficient appliances, with EE-index and housing type being the strongest of these predictors while income is weaker. From our analysis of the EE-index, we identify that specific daily actions are correlated with investment in efficient household appliances. Furthermore, by analyzing the correlations within the EE-index, we found that respondents generalize their EE behaviour by appliance type and that efficient end-use behaviours are related with particular living conditions, e.g., housing type.

By providing empirical results on the influence of both socioeconomic and behavioural variables on consumer choice, the paper narrows the knowledge gap on household energy consumption behaviour and broadens knowledge on the drivers of purchasing high-labelled household appliances.

The remainder of the paper is organized as follows. In [Section 2](#), we review the literature on household energy consumption behaviour. In [Section 3](#), we introduce the survey data and describe the consumer investment model based on logistic regression. In [Section 4](#), we present the model estimation results and discuss the effect of different socioeconomic, demographic, and behavioural variables in the choice of EE appliances. We conclude in [Section 5](#) by drawing practical policy suggestions based on our findings.

2. Literature review

The study of household energy consumption behaviour focuses on understanding the reasons why end-users adopt particular consumption patterns. Four key questions are the focus of debate: (1) What is driving energy consumption; (2) How does lifestyle and habits influence the use of energy; (3) Which models can closely describe the consumer behaviour; and (4) Which policies can be proposed to decrease total energy use.

Socioeconomic characteristics are often cited as significant drivers of household energy consumption. Global research programs, conducted via household surveys, suggest that demographic and socioeconomic factors, such as income level, ownership, dwelling type and number of inhabitants, are correlated with the energy use ([De Almeida et al. 2011](#), [Bedir et al. 2013](#), [Wyatt 2013](#), [Zhou and Teng 2013](#), [Hayn et al. 2014](#), [Huebner et al. 2015](#), [Murphy 2014](#), [Jones and Lomas 2016](#), [Zhou and Yang 2016](#), [Girod et al. 2017](#)).

Beyond these factors, researchers stress the focus on energy consumers' end-use behaviour. Lifestyle and habits impact the final use of energy, most often in an unpredictable way (Zhou and Teng 2013, Gram-Hanssen 2014, Frederiks et al. 2015). Empirical research indicates that behaviour (or comfort preference) is related to the socioeconomic characteristics, including income (Vassileva et al. 2012), household type (Bedir et al. 2013, Huebner et al. 2015, Jones and Lomas 2016, Girod et al. 2017), family age composition (Mills and Schleich 2012), and employment (Hayn et al. 2014). Additionally, ulterior motives influence behaviour such as environmental consciousness (Gram-Hanssen 2014, Zhou and Yang 2016), environmental innovation intention (Long et al. 2017b) and attitude towards environmental behaviour (Long et al. 2017a) which, ultimately, has an impact on consumer's intentions (Ajzen 1991, Abrahamse and Steg 2009).

The aforementioned socioeconomic and behavioural characteristics are also studied as relevant reasons prompting consumers to choose high-labelled appliances. The results from a 2014 Organisation for Economic Co-operation and Development (OECD) survey on household environmental behaviour and attitudes identified potential factors behind consumer choices on energy efficiency investments as home ownership, income, social context, and household energy conservation practices (Ameli and Brandt 2015). Various analyses, based on different surveys in an international context, resulted in similar conclusions (Mills and Schleich 2010a, Gaspar and Antunes 2011, Qiu et al. 2014, Jacobsen 2015). In the Danish context, although previous studies have used survey results to assess the factors influencing household electricity consumption (Bartiaux and Gram-Hanssen 2005), efficient utilization of household appliances (Nielsen 1993), and patterns of domestic electricity use (Gram-Hanssen et al. 2004), to the best of our knowledge none has focused on purchase propensities in relation to energy efficient household appliances. Moreover, while other studies made use of energy-related behaviours and habits in consumer models (Gaspar and Antunes 2011, Kavousian et al. 2013, Krishnamurthy and Kriström 2015, Ameli and Brandt 2015), none has performed an extensive investigation of such energy end-use behaviours. In fact, in this paper we analyze interrelations among various behavioural components to investigate which actions make the consumer more likely to invest in EE appliances and if specific end-use behaviours are related to particular living conditions.

The science of consumer behaviour and energy literacy—that is, the ability of consumers to make rational decisions on EE investments (Brounen et al. 2013)—adopts and employs energy efficient behavioural measures, equipment, intentions and planned behaviour (Abrahamse and Steg 2009, Ajzen 1991, Long et al. 2017a). Often, when designing appropriate tools, the economic theories on consumer's choices are based on rational maximizing models describing how consumers should choose (normative theories) rather than how they do choose (descriptive theory). Results from orthodox-economic models where the consumer is depicted as a robot-like expert, can thus be a poor prediction of the actual behaviour of the average consumer (Thaler 1980). Realistic empirical studies provide evidence that consumers do not always act rationally and their choices are influenced by a myriad of non-rational influences. Thus,

consumer behaviour models, if wrongly formulated, can lead to misleading outcomes (Thaler 1981). Realistic consumer behaviour is crucial when designing proper tools for predicting or describing consumer choices. With this in mind, in this paper we built a logistic regression model—validated using different statistical tests—that accounts for socioeconomic and demographic variables as well as behaviours, trying to capture non-rational influences on consumer choices. This model provided us with interesting insights on the characteristics influencing the decision process of the consumers when purchasing high-labelled household appliances.

Studies investigating the success of policies implemented, such as the ENERGY STAR in the U.S. or A-G energy labels in Europe, show that financial incentives (subsidies), energy audits, minimum energy performance standards (MEPS), energy literacy and reduced value added taxes for EE technologies contribute positively to the uptake of energy efficient appliances and replacement of old equipment (De Almeida et al. 2011, Mills and Schleich 2012, Brounen et al. 2013, OECD 2013, Murphy 2014, Krishnamurthy and Kriström 2015, Datta and Filippini 2016, Zhou and Yang 2016, Girod et al. 2017). Similar to MEPS, mandated energy efficiency measures (for new equipment) coupled with properly designed and implemented public awareness campaigns results in legitimate energy savings (Wyatt 2013, Frederiks et al. 2015, Young 2008). A recent analysis on the Danish market, for example, showed that new labelling schemes lead to a notable increase in the sales of EE appliances (Bjerregaard and Framroze Møller 2017). However, in contrast, some of the literature on the efficacy of policies and information campaigns showed that a large portion of the population is still unaware of energy labelling (De Almeida et al. 2011, McMichael and Shipworth 2013, OECD 2013, Zhou and Yang 2016) or energy conservation behaviour measures (Brounen et al. 2013). Finally, recent research has shown that policies and actions need be tailored to specific households, tenants and technologies since a generalised approach might not work as efficiently and lead to less than desirable outcomes (Vassileva et al. 2012, Frederiks et al. 2015, Krishnamurthy and Kriström 2015, Jones and Lomas 2016, Chai and Samatha 2017, Girod et al. 2017). Following this literature, in this paper we suggest improved energy efficiency policies that indeed target key demographics identified through our purchase propensity analysis.

3. Data and model

The primary dataset analysed in this study is the DEA’s bi-annual survey “El-model Bolig”, the goal of which was to collect information about consumers’ purchasing and use of household appliances. Although the survey is performed every two years, the 2012 set was chosen over the most recent dissemination because the 2012 survey uniquely contains questions on the efficiency labelling of major household appliances. The total number of survey respondents, or observations, was 2053; however, we removed 337 observations due to missing values giving a final sample size of $n = 1716$. The survey comprises about

340 questions in total. The number of questions for each respondent, though, depends on logical operators and reported ownership—for instance, a respondent without a freezer will not be asked questions about its usage. The sampling was conducted under random block design as to approximately represent Denmark’s geographic and housing category distributions (apartments, farmhouses etc.), and was not stratified with respect to other socioeconomic and demographic variables.

3.1. Socioeconomic, demographic, and behavioural variables

The primary variables of interest from the survey are the socioeconomic and demographic variables listed below, chosen with the intention of predicting investment in the highest EE labelling.

- Age: an ordered categorical variable whereby Age 1 = 18–29 years, Age 2 = 30–39 years, Age 3 = 40–49 years, Age 4 = 50–59 years, and Age 5 = 60 years or older.
- Quantity of inhabitants: recorded as a continuous variable in the original survey dataset, counting the total number of adults and children living in the respondents’ household.
- Housing type: four choice levels given by apartment, farmhouse, single/detached (referred to as “single” henceforth), and townhouse.
- House size: an ordered categorical variable with 8 levels from less than 39 m^2 to over 200 m^2 interior floor space.
- Year built: an ordered categorical variable with 6 levels for the year a house/apartment was constructed, ranging from before 1900 to 2001 or newer.
- Income: gross household income (before taxes).
- Investments in EE appliances, that is, the labelling of most recent purchased appliance.

Beyond questions about appliance investment and ownership, the survey contains a wealth of questions regarding end-use behaviour for appliances and heating systems. Several of these questions can capture whether the consumer performs daily activities classifiable as energy efficient behaviour. Questions like “How full do you fill your clothes/washing machine on a normal use” or “Do you turn off the power socket during the night” have thus been used (see the [Appendix](#) for the full list of questions included in the index). We incorporated these unique responses by computing a behavioural energy efficiency index, abbreviated throughout the paper as EE-index. The combination of these variables in the index represents a level of energy consciousness and intent to save energy for both electricity and heating. For example, managing heating between night and day (turn heat down at night) or removing power sockets after use are all positive EE indicators.

To compute the EE-index, we assigned each question an equally weighted point: 1 for positive energy saving behaviour, 0 for poor behaviour. Although in theory different actions can result in different levels of energy savings, the survey does not contain detailed appliance and action characteristics (e.g., appliance type, capacity, consumption, time of use) that enable directly quantified savings nor define action-specific weights. All questions are weighted equally with scores normalised per each respondent’s appliance portfolio. Of course, not all respondents own oil or natural gas heating, for instance. Thus, to compare respondents with differing levels of appliance ownership, the individual scores were standardized by their individually maximum possible score (see the [Appendix](#) for the percentage of respondents eligible for each question). The score is defined for each consumer $j \in \{1, \dots, n = 1716\}$ in the sample as

$$\text{EE-index}_j = \frac{1}{Q_j} \sum_{i=1}^{\bar{Q}} Z_{ij},$$

where $\bar{Q}$ is the total number of questions, Q_j is the count of eligible questions for respondent j , and Z_{ij} equals 1 for a point awarded to respondent j for question i . Eligible questions Q_j are counted according to the appliance ownership profile of respondent j . For example, a respondent without a washing machine will not be scored nor counted in Q_j for questions pertaining to washing machine use. The index is on a $[0, 1]$ scale. Of course, more appliances (greater summed Q_j) will decrease the marginal weight of each point, that is, the index is less sensitive to those with many appliances or eligible questions.

The survey also contains additional questions regarding profession of respondent and spouse, lighting system and electricity consumption. In addition to the EE-index, we thus calculated:

- a “job index” whereby the respondents’ professions were ranked per average years of training or education on a scale from 1 to 10 for the job categories included in the survey. This job index was then considered a potential predictor of EE appliance investment.
- a “light score” assessing the respondents’ ownership of EE lighting. The light score is calculated as the ratio of reported saving light bulbs, or EE lighting (for instance, LEDs and compact fluorescent lamps), to the total sum of both EE lighting and traditional incandescent light bulbs. Thus, the score is normalised on a $[0, 1]$ scale.
- the “know el.”, representing a non-socioeconomic binary variable equalling 1 if the respondent reports to currently know her annual electricity consumption, and 0 if the respondent reports not knowing.

In [Table 1](#) we present a summary of the explanatory variables used in the model, and their characteristics. Lastly, we are interested in the investments in EE labelled appliances. The survey asked each respondent to state the energy labelling of a given appliance they report to own or which they had recently purchased. The full set of appliances in the survey are: combination washer-dryer, washing

Table 1: Explanatory variable name, type, and description

Explanatory variable	Type	Description
Qty. inhabitants	continuous	Number of household inhabitants, from 1 to ≥ 8
House type	categorical	4 levels: apartment, farmhouse, single house, townhouse
House size	categorical	8 levels, from less than $39 m^2$ to over $200 m^2$
Year-built	categorical	6 levels, from < 1900 to ≥ 2001
Age	categorical	5 levels: 18–29, 30–39, 40–49, 50–59, 60 or older
Income	continuous	Gross household income, in $[0, +\infty]$
EE-index	continuous	Behavioural energy efficiency index, in $[0, 1]$
Job index	continuous	Average years of education/training, in $[1, 10]$
Light score	continuous	Energy efficiency lighting ownership, in $[0, 1]$
Know el.	categorical	Knowledge of own electricity consumption, in $\{0, 1\}$

machine (standalone), dryer (standalone), dishwasher, combination fridge/freezer, fridge with integrated box freezer, fridge (standalone), chest-freezer, and a standing freezer. For some of the appliances (e.g., chest-freezer) too few respondents reported ownership, not allowing us to make a meaningful analysis per each individual appliance. Thus, the set is aggregated to a singular latent variable: “for her most recent purchase in any one of these appliances, has the consumer invested in the rating A+ or higher?” Because of such aggregation, 68% of respondents reported EE investment while 32% did not. The rest of the paper focuses on identifying which of the explanatory variables best distinguish these two groups of consumers. We first present descriptive statistics for the modelling sample and compare them against national statistics.

3.2. Dataset validation

To verify that our dataset provides a good representation of Denmark, we compared the distribution of the socioeconomic factors in our modelling sample against the 2012 national statistics from Statistics Denmark (DS; see [DS 2017](#)).

The age distributions of the survey sample and DS are displayed in [Figure 1](#). The distribution of the survey sample is slightly skewed towards middle and elder ages since, typically, it is the head of the household who is answering the survey. This explains why age level 1 is only 7% of the survey sample while age level 4 is 32%. The remaining classes are similar to those of DS.

The survey distribution of the number of inhabitants is displayed in [Figure 2](#) and is deemed fairly representative. Some differences compared to the national statistics hold for one and two inhabitants per household, but overall are acceptable.

Regarding housing age, [Table 2](#) shows that the 2012 distribution of year built in the survey sample closely matches that of official registries, thus, it is representative of Denmark.

Figure 1: Age of respondents: survey sample and national statistics

Figure 2: Quantity of inhabitants: survey sample and national statistics

Table 2: Housing year built: survey sample and DS.

Year built	Sample	DS
Before 1900	8%	9%
1900-1925	11%	12%
1926-1950	15%	16%
1951-1975	34%	32%
1976-2000	25%	23%
2001 or newer	7%	8%

The variables for which a comparison was not possible include housing type and income. Regarding housing type, the categories used in the survey diverge from those recorded in the official statistics. For example, DS includes student housing and cottages, which are ignored by the survey. Moreover, DS includes some detached housing types in its farmhouse category, whereas the survey farmhouse category explicitly pertains to properties with land holding. As a consequence, a comparison between DS and the survey housing type distributions would be misleading. Regarding income, the survey originally reported the total household income before taxes, whereas DS reported the “disposable equivalised income”, which is the household income after taxation divided by a weighted number of adults and dependents living in the given household (DS 2015). Therefore, any comparison would be inaccurate due to the different

income calculation and the inability to assume taxation rates on the survey's gross incomes and convert gross incomes into disposable incomes.

3.3. Consumer investment model

Consumer behaviour in relation to investments in household energy efficient appliances is evaluated with a discrete choice model. The merit of this modelling framework is the ability to empirically test the predictive strength of the survey's explanatory variables. Specifically, we use a logistic regression model that is constructed as follows. The EE investment is considered as a binary outcome Y ($1 = \text{investment}$, $0 = \text{no investment}$) and the model assumes that

$$\begin{aligned} \text{logit}(P(Y = 1 | X_1 = x_1, \dots, X_n = x_n)) &= \log \frac{P(Y = 1 | X_1 = x_1, \dots, X_n = x_n)}{1 - P(Y = 1 | X_1 = x_1, \dots, X_n = x_n)} \\ &= \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n, \end{aligned}$$

where $X = [X_1, \dots, X_n]$ represents the vector of all explanatory variables discussed in [Subsection 3.1](#) (age, income, type of house, EE-index etc.) and $\beta = [\beta_0, \dots, \beta_n]$ the weight vector. The dependent variable Y represents a single investment in an A+ or higher labelled appliance among a set of nine appliances listed in the survey (the set of appliances is considered as aggregated to maintain an adequate sampling size and distribution, as discussed in [Subsection 3.1](#)).

To estimate the model, the weights β are fitted through logistic regression on the survey data via the logit maximum likelihood function. Then, given the estimates $\hat{\beta} = [\hat{\beta}_0, \dots, \hat{\beta}_n]$ and the characteristics of a consumer $x = [x_1, \dots, x_n]$, the resulting predicted joint-probability of EE appliance investment π , or the probability that $Y = 1$, is computed as:

$$\pi = P(Y = 1 | X_1 = x_1, \dots, X_n = x_n) = \frac{\exp(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_n x_n)}{1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_n x_n)}.$$

4. Results and discussion

4.1. Model estimation

[Table 3](#) reports the outcome of the multivariate regression consumer investment model, computed with the software R. The final regressors are chosen, according to common practice, using a backwards elimination process until the model only contains statistically significant explanatory variables ([Derksen and Keselman 1992](#)). The factor levels age group 1 and apartment are considered model reference levels and thus do not respectively have model terms. The joint probability for age group 1 and apartment is considered to be the estimate of the model intercept, or the probability of investing when all other variables are set to 0. One can see that the explanatory variables positively affect the total probability of EE investment choice. For example, assuming all other variables constant, by increasing income of one

Table 3: Consumer investment model estimates. Significance codes for p-values: 0.001 ‘***’, 0.01 ‘**’, 0.05 ‘*’, 0.1 ‘.’

Explanatory variable	$\hat{\beta}$ estimate	Std. error	p-value	Significance level
Intercept	-2.001	0.295	< 0.001	***
Income	0.076	0.030	0.013	*
Light score	0.480	0.180	0.007	**
EE-index	0.762	0.303	0.010	*
Know el.	0.221	0.127	0.082	*
Qty. inhabitants	0.198	0.066	0.002	**
Farmhouse	0.673	0.230	0.003	**
Single house	0.550	0.142	< 0.001	***
Townhouse	0.304	0.173	0.079	.
Age group 2	0.674	0.267	0.011	**
Age group 3	0.683	0.245	0.005	**
Age group 4	0.712	0.242	0.003	**
Age group 5	0.849	0.244	< 0.001	***

unit (100,000 DKK), the expected odds of choosing an EE appliance will be 1.079 times greater (since $\exp(0.076) = 1.079$).

The values in [Table 3](#) represent the outcome of the final model only. Other explanatory variables, as house size or job of the respondent, were included in a previous larger model but discarded in the backward elimination process. [Table 4](#) reports the dropped explanatory variables (that is, with p-values higher than 0.1) along with their $\hat{\beta}$ estimates. The dropped model estimates show that the year in which the building was built, the size of the households and the job of the respondent appear not to be relevant characteristics to predict selection of EE appliances.

Table 4: Consumer investment model estimates for the dropped explanatory variables.

Explanatory variable	$\hat{\beta}$ estimate	Std. error	p-value
Year-built	0.045	0.044	0.313
House size	0.005	0.032	0.867
Job index	0.014	0.017	0.410

The final model adapted for the analysis has been validated to prove the consistency of the findings and assess the reliability of the model. Different criteria have been used for model diagnostics:

1. The Hosmer-Lemeshow’s Goodness of Fit test is widely used in logistic regression to prove the fit between the model and the data ([Hosmer and Lemeshow 1980](#)). It tests against the null hypothesis H_0 of observed investment rates matching the predicted ones, and returns a p-value. A p-value

lower than 0.05 suggests that the model does not adequately predict the binary outcome of Y and should be rejected. The outcome of the test was a p-value of 0.33, meaning there is no evidence to reject the model.

2. The McFadden R-squared test is similar to the R-squared test but based on the rho-squared measure (McFadden 1977). The test returns a value representing the predictive ability of the fitted model compared to the null model, that is, a model with only an intercept and no covariates. According to the test, any result between 0.2 and 0.4 represents an excellent fit. The outcome for our model was a value of 0.21.

4.2. EE-index and light score

We summarise the most important variables in the EE-index composition in the form of a heatmap in Figure 3. The EE-index variables are divided by housing type and, for brevity, they are listed in their coded format (see the Appendix for full description). The graph reports the ratio r whereby the numerator is the total sum of points for question i for all of respondents in housing type k , and the denominator is the sum of eligible respondents per question, per housing type. The ratio r allows for relative comparisons within and between each housing type: a block at 100% indicates that all respondents of housing type k received points for that particular question. For example, question X587 has one of the greatest relative importance for farmhouses (indicating whether or not the respondent turns her natural gas heating to summer mode).

Figure 3: Heatmap with ratio r showing relative percentage of EE-index points by housing type.

We noticed that the housing types differ with respect to the EE-index and its composition. Some questions as X359 and X401 are relevant for all housings types with scoring close to 100% (one point awarded if the dishwasher and washing machine, respectively, are filled to over 50% per average use). In contrast, question X334 is relatively less important for apartments (one point awarded if owners of standalone washing machines normally wash at the highest RPM setting). Some questions carry little weight in the final score calculations since they pertain to specific heating technology behaviours such as X666 (a point awarded if the respondent applies a normal step circulation pump in her radiant heating system).

Figure 4 shows the correlation between each of the EE-index questions. The purpose of the graph is (i) to assess whether performing a specific energy end-use action is correlated to other actions, and (ii) to identify overall trends in end-use from the survey sample data.

Figure 4: Correlation matrix of all EE-index questions

An examination of these correlations reveals that there are several clusters of positively correlated variables, indicated by the dark blue colours. For example, one cluster is for variables X317, X318, and X322, all related to dryer usage. Another positive cluster includes X487, X490, X523, X532, X551, and X552 which pertain to whether or not the respondent removes a specific appliance from the power socket after use. Also, a cluster includes variables X664, X665, and X666, pertaining to behaviour with heating technologies, such as turning your circulation pump to summer mode. The prevalence of these positively correlated clusters suggests that consumers generalise their behaviour by appliance. For example, a consumer who normally washes clothes at a low temperature is more likely to report EE conscious behaviour on remaining washing machine questions. The correlation analysis also shows that there are few negatively correlated variables.

The EE-index scores, shown in Figure 5 (left), present a distribution with a mean of 0.49 and a standard deviation of 0.17 which resembles a normal distribution. In Figure 5 (right) we also display the distribution of the light score. The score is highly left tail skewed. Moreover, more than 30% of respondents reported having only EE lighting (no incandescent lights), explaining the peak corresponding to an index value in the interval $[0.9, 1]$.

Figure 5: Probability distributions for EE-index (*left*) and light score (*right*).

4.3. Purchase propensity curves

Propensity curves have been computed to study how the predicted probabilities in EE appliance choice change per variations in the explanatory variables. The curves are evaluated varying one variable at a time, while keeping the others fixed to the following values: income is kept fixed to 400,000 DKK, EE-index, light score and know el. are kept fixed to 0.5, number of inhabitants to 2 and age to class 3.

Figure 6 shows the development of the expected probabilities for different levels of income. The trends suggest that the higher the income, and consequently wealth, of the respondent, the higher is the probability that the same respondent will choose more efficient household appliances when investing. The curves are reported for the different type of dwellings to simplify the understanding of the analysis. The differing levels (intercepts) of the curves illustrates the importance of the house type factor: the propensity curves for choosing energy efficient appliances for farmhouses and single houses are on average more than 10% higher than apartments, and up to 15-17% higher for low income levels.

Figure 6: Predicted probability of investing in EE appliance by income.

Figure 7 and Figure 8 report the development of the probabilities for the number of inhabitants and EE-index, respectively. The figures show that a higher number of people living in the dwelling, as well as a higher EE-index, results in a greater predicted propensity for choosing energy efficient appliances. The curve levels for different housing types are consistent with those of Figure 6, with farmhouses and single houses being substantially higher than apartments.

Figure 7: Predicted probability of investing in EE appliance by inhabitants.

Figure 8: Predicted probability of investing in EE appliance by EE-index

Figure 9 and Figure 10 illustrate respectively, the point-wise estimated probability for varying age and housing type, along with 95% confidence intervals. The results suggest that older respondents have a higher propensity to choose energy efficient appliances, as only the groups 2 through 5 differ significantly from group 1. Likewise, the range of the confidence intervals varies for the different type of dwellings. The apartments and single family houses present larger variation compared to other housing types. Also, the predicted probability is the highest for farmhouses and the lowest for apartments.

The probabilities of choosing EE investments resulting from the model can be perceived as generally high (e.g., the average rates are above 50-60%). This is explained by the original distribution of the

Figure 9: Predicted probability of investing in EE appliance by age.

Figure 10: Predicted probability of investing in EE appliance by housing type.

reported survey data.

Finally, we assessed the robustness of the model using a marginal effect plot with a bootstrap error, displayed in [Figure 11](#) for the different variables. This is employed to assess the sensitivity of the originally computed model estimates to statistical assumptions. The bootstrap method draws 1000 random samples from the original survey data, recalculating model estimates 1000 different times. If the bootstrapped estimates and standard errors deviate substantially from the original values, there is evidence of major violations of statistical assumptions (that is, collinearity or low predicting power resulting from few observations). Like the original coefficients, the marginal effects can be seen as partial derivatives of total joint-probability function. The average of the re-sampled marginal effects is the midpoint, while the tails illustrate the 95% confidence interval.

The bootstrapping shows that the income is hardly significant and casts some doubt about the strength of income to predict EE investment choice, compared to the more qualitative EE-index and house setting. Given the results, farmhouses are more likely to choose EE appliances when compared to other house types.

Figure 11: Marginal effects with bootstrap errors of the explanatory variables

4.4. Discussion of the results

The positive correlation between household income and EE appliances adoption concurs with previous studies (Long 1993, Mills and Schleich 2010b, Sardianou and Genoudi 2013, Ameli and Brandt 2015). However, our results show that income is not one of the strongest predictors to EE appliance purchases when compared to other variables considered. This finding might be specific to Denmark, a country with relatively high income and social welfare; in other countries, household income could possibly reveal to be the strongest predictor. Moreover, given the available data and logistic modelling assumptions, there is no convergence to 100% probability of investment for the highest income classes. In fact, even the highest earning consumers are unpredictable in their choices, and as mentioned, driving factors extend beyond energy efficiency to include cost, quality, brand, and functionality (Gaspar and Antunes 2011, Baldini and Trivella 2017).

The building type is one of the strongest predictors of EE appliance choice. In particular, the values of the estimates in Table 3 show that farmhouses and single family homes residents are significantly more likely to choose EE investments than apartment residents. The related purchase propensity curves in Figures 6–8 also highlight the relevance of the household type for this analysis. The curves vary because consumers living in different housing types, on average, own a different number of household appliances and have different levels of wealth and lifestyle. This translates into an energy end-use and attitude towards energy efficiency and environment that can vary substantially among these groups. Apartments, for example, are associated with a lower probability of purchase because they are often rented out, and renters are less sensitive to energy-efficiency investments due to the short length of the stay (see our related

discussion in [Subsection 5.2](#)). In contrast, farmhouse dwellers typically own the property. Moreover, they are in general more sensitive towards energy-efficiency because farmhouses are, on average, larger than apartments and contain more appliances thus incurring higher expenses for electricity and heating. This leads to a higher purchase propensity as also confirmed by our results. Consistently with this discussion, single houses and townhouses lie somewhere in between as shown in [Figures 6–8](#). Previous studies focusing on more specific investments (heat pumps, EE windows) agree with such correlation ([Mills and Schleich 2009](#), [Michelsen and Madlener 2012](#), [Ameli and Brandt 2015](#)). More technical housing variables such as house size or year of construction appear instead to be insignificant.

Regarding age, respondents younger than 30 years are significantly less likely to invest in EE appliances. Other studies suggest that age, as a predictor, is sensitive to specific technologies: older consumers are more likely to invest in EE light bulbs ([Mills and Schleich 2010b,a](#)), renewable energy technologies as wind mills and solar photovoltaic ([Willis et al. 2011](#)), but not heat pumps ([Mills and Schleich 2009](#), [Willis et al. 2011](#), [Michelsen and Madlener 2012](#)).

On the quantity of inhabitants, the estimates confirm the positive relationship: the odds of investing in EE appliances increase with inhabitants. Several other studies achieved a similar conclusion ([Mills and Schleich 2010a, 2012](#), [Ameli and Brandt 2015](#)). A larger household inhabitancy results in greater and more intensive energy consumption; reasonably, these households would have a greater incentive to invest in energy savings assuming rational economic behaviour ([Bartiaux and Gram-Hanssen 2005](#)).

The variables light score and know el. result in comparatively strong, positive parameter estimates. Respondents with more EE lighting and those who report knowing their own consumption choose more efficient appliances at the moment of purchase; this suggests that one EE conscious behaviour begets the next.

The EE-index’s high significance (and especially large parameter estimate) shows how daily energy conservation actions such as turning off the power socket by night and adapting the heating system to the seasons strongly predict the choice of investing in EE appliances. The positive relationship could be expected since it alludes indirectly to environmental stewardship and energy savings attitudes (and also economic savings). Nevertheless, this paper provides empirical evidence that energy end-use daily actions are correlated with EE investment. Furthermore, the correlation matrix of all the EE-index questions, showing the correlation between the pertinent energy-savings end-uses, has highlighted that particular EE conscious behaviour begets some others. Thus, another practical finding from the EE-index analysis is that respondents generalize their EE behaviour by appliance group.

The correlation between overall high EE-index scores and A+ label investment poses a future research question: do respondents generalize their appliance specific behaviour because they purchased an A+ label (i.e., I buy green therefore I act green), or do respondents seek A+ appliances because they perceive their previous behaviours as green and efficient. One avenue for future research could be to test this

relationship through a combination of surveying and direct end-use observations. Observational data is now possible through advanced metering infrastructure and smart appliances. Though there are privacy concerns, observational data would greatly complement a survey sampling which are inherently prone to bias and response errors.

5. Conclusions and policy implications

The study aimed to understand which characteristics lead consumers to choose energy efficient appliances at the moment of purchase. Using data from a DEA survey and a statistically sound logistic regression model, socioeconomic, behavioural, and housing characteristics were found to be highly significant when explaining the choice of investments in EE appliances, with housing type and EE-Index being the strongest of these predictors. Particular focus was given to the EE-index, combining all behavioural characteristics pertinent to energy savings, and proving that consumers who performed energy conservation actions regularly were more likely to choose EE appliances.

The outcomes of the study spark suggestions about relevant policy measures. Even though energy efficiency continues to rise among most appliances (Barbieri and Palma 2017), there are still large groups of the population that for many reasons do not invest in EE appliances. Given the importance of socioeconomic characteristics highlighted by our results, existing labelling directives should be assisted by product designs and promotion targeting citizen with such characteristics, for instance, using subsidised rebates and discounts for consumers who are least likely to undertake the investment. Following the results of this work, we identified three major points that should be addressed while outlining energy saving policies: (i) future development of appliance ownership and population housing, (ii) building ownership versus renting, and (iii) evolution of information campaigns.

5.1. Trends of appliance ownership and population housing

As policies are meant to be effective in the long term, it is fundamental to consider the future evolution trends of the appliances. The online tool *El-model Bolig - prognose* (El-model buildings - prognosis, in English; DEA 2017b), developed by DEA, provides forecasts of appliance ownership based on the same 2012 El-model Bolig survey data employed in this analysis, as well as other survey editions (2006, 2008, 2010, 2012 and 2014). The tool allows user-specified inputs and can produce either linear or Gompertz forecasts of appliances' characteristics such as lifetime, sales, quantity, energy use and sales number. Figure 12 reports Gompertz forecasts for the sales of five of the major energy intensive household appliances for apartments (*left*) and detached houses (*right*), for the period 2017-2050. The forecasts do not contain labelling information, but provide a projection based on simple historical ownership data.

The projections for the apartments and detached housing illustrate increasing ownership, suggesting that residents of apartments and detached houses should be targeted for energy efficiency policy related

Figure 12: Sales forecasts of different appliance categories for apartments (*left*) and detached houses (*right*).

actions. The raising trend of appliances for these housing types is largely due to an underlying increase in Danish urban populations and housing centres (Trading Economics 2017). Broadening the scale, this trend is consistent with the recent global trends showing that world’s population is increasingly urban with more than half living in urban areas (UN 2014). As urban populations and the number of urban centres continue to grow, rural populations are expected to decrease. These trends entail a shift of housing conditions to more apartments, implying a change in the energy consumption.

Considering these trends and the results of our study, the authors suggest that policy makers emphasise energy efficiency awareness campaigns for urban citizens, for example, by establishing energy audits to sensitise these users on the contribution of each appliance to total household energy consumption and on the benefits that specific energy efficiency investments would bring in the short and long run. With the underlying assumptions that the population does not choose EE appliances partly due to lack of knowledge regarding the benefits of energy saving, subsidies should thus be directed to increase the awareness of energy efficient appliance choice with additional focus on end-use behaviour. This should lead to more conscious energy use and savings, which in turn, as suggested by our findings, is correlated to a higher uptake of energy efficient appliances.

5.2. Building ownership versus renters

The status of home ownership should also be considered for targeted information campaigns. Intuitively, renters are less likely to choose EE appliances as it is improbable that such investments will break-even; in other words, renters would not enjoy the long run economic benefits of investing in energy efficiency. In fact, the payback time of investments in EE appliances is usually in the range of 5-25 years (Baldini and Trivella 2017) while the average stay for a renter is shorter. Also, the lifetime of new appliances generally overruns the stay of renters within the building or even in the city and furthermore, particularly for large appliances such as fridge or dishwasher, the transfer to a new location implies logistic challenges. Empirical analyses have also found that renters were significantly less likely to invest

in EE refrigerators, clothes washers, dishwashers, and lighting, for example (Davis 2012, Krishnamurthy and Kriström 2015). Special focus should be on designing subsidies for short term renters, like students, who are usually the least likely to undertake high upfront investment. In addition to living in rented apartments, students have low or no income and are generally younger than 30, all being socioeconomic factors leading to a low adoption rate of EE investments, as indicated by this study. To this end, dwelling owners could benefit from discount rebates when purchasing high-labelled household appliances for renting purposes. This would consequently help short term renters and in particular students who would enjoy EE appliances without bearing high investment cost.

In Denmark, home ownership levels are geographically disparate, being higher in countryside municipalities (50-65%) and lower in the main cities (e.g., only 20% in Copenhagen) (Kristensen 2007). Moreover, population forecasts project growth rates of 5-10% across Danish urban centres contrasted to decreasing population rates in rural Western areas (DS 2017), supporting our overall recommendation of information campaigns directed especially towards apartment renters.

5.3. *Evolution of information campaigns*

In the past years, Denmark has been active concerning energy efficiency awareness campaigns. Beyond the EU labelling scheme, Ecodesign requirements, and other broad-stroke energy savings targets, there are several Denmark-specific examples pertinent to this study. *SparEnergi.dk* (DEA 2017e) represents Denmark government’s most advanced platform for helping consumers to make energy savings decisions. Launched in November 2013 by DEA, the website contains a wide range of information on how to interpret the current energy labelling for appliance groups (washing machines, dryers, fridge and freezers, lights), along with minimum labelling recommendations (e.g., A for combined washing machine/dryers, A++ for standalone dryers). The guidelines also focus on the size of the appliances and the monetary and energy savings resulting from the choice of a more efficient appliance compared to another. The platform provides suggestions about consumers’ end-use behaviour; for example “fill the machine completely”, “turn down the temperature”, “short program”, “clean filters”, “leave room for ventilation” are all listed as means to reduce the energy consumption and achieve savings.

Therefore, the problem seems to be not the information itself, or lack of, but rather dissemination. Policy makers should thus improve the means of communication regarding energy efficiency. With respect to the degree of labelling influence, a recent analysis of EU-member residential energy efficiency policy over the period 1974-2016 casts doubt (Filippini et al. 2014). The study indicated that information campaigns such as labelling did not have a significant effect in promoting energy efficiency improvements over that time period. This result, combined with the findings of our study, suggests that the focus for future policies should extend beyond developing the labelling metric itself, to considering what that metric actually means to the consumer in the moment of purchase.

A personalised app or a feature on a merchant website could convey a simplified trade-off between energy efficiency and cost, such as payback times on a price-premium, for instance, going from a dryer label A to A+++. On the matter, *SparEnergi.dk* has just recently started operating free counselling services through popular social medias (Facebook) and call centres (DEA 2017a, Viegand Maagøe 2017), to answer questions related to household energy consumption. Given the recent progress and broad access to technology, information campaigns should extend to technology-based platforms such as mobile apps or social media so that they can reach a broader population. For example, local administrations could create and manage a municipality-based social media page, explaining the main factors contributing to the local household energy consumption and providing recommendations on how to reduce it. After the first sparks, the “neighbours effect” should induces the learning process and the dissemination of knowledge through families and networked communities, leading to a likelihood increase of adoption rates (McMichael and Shipworth 2013). Also, information and communication technologies can facilitate the transition towards a smarter use of energy by increasing consumer awareness on the impacts related to the number of devices as well as the importance of energy efficiency (Røpke et al. 2010, De Almeida et al. 2011, Zhou and Yang 2016). For example, smart meters can play an important role by providing visual information about the disaggregated consumption of household appliances or suggesting the consumer to conserve energy during peak hours (Allcott 2011).

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Appendix. EE-index composition

Table 5 details the rationale and summary of all the variables included in the EE-index. In particular, the table reports variable name, code, and the total number of respondents that are eligible for scoring, meaning that they own the appliance the question refers to and thus can be scored accordingly.

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Table 5: Summary of EE-index questions and scoring rationale

Code	Scoring rationale	Eligible	% eligible
X212	Washing machine temp 29°C or less on average (combi washer-dryer)	52	3%
X2559	Washes clothes at 70°C less 1 time/wk	1442	84%
X257	Remove PC from power socket	1057	62%
X259	PC set to automatically shut down	1057	62%
X317	Dryer used at highest RPM on average	52	3%
X318	Air dries clothes in summer more than using electric dryer (combi washer-dryer)	52	3%
X322	Dryer filled over 50% on average	52	3%
X334	Washing machine used at highest RPM	1442	84%
X342	Air dries clothes in summer more than using electric dryer (standalone dryer)	940	55%
X350	Washing machine temp 29C or less on average(standalone dryer)	1299	76%
X359	Dishwasher filled over 50% on average	1298	76%
X401	Washing machine filled over 50% on average (standalone washer)	1442	84%
X487	Removes TV from power socket after use	1689	98%
X489	TV set to automatically shut down	1689	98%
X523	Removes laptop from power socket after use	1448	84%
X532	Removes printer from power socket after use	1539	90%
X535	Removes scanner from power socket after use	173	10%
X551	Removes router from power socket after use	1716	100%
X552	Removes other PC/misc electric equipment from power socket after use	1716	100%
X580	Temperature setpoint at 21°C or less	1687	98%
X581	Temperature setpoint regulated night/day	1649	96%
X583	Turns off electric floor heating in summer	175	10%
X584	Turns off radiant floor heating in summer	345	20%
X585	Turns oilfloor to summer-mode	135	8%
X586	Turns oil/wood heating to summer-mode	11	1%
X587	Turns natural gas heating to summer-mode	192	11%
X628	Uses air-to-air heat pump for cooling	72	4%
X664	Changes circulation pump's step in summer	760	44%
X665	Regulates (up/down) circulation pump	522	30%
X666	Has a normal step circulation pump	256	15%

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