The Impact of Green Framing on Consumers’ Valuations of Energy-Saving Measures

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The impact of green framing on consumers’ valuations of energy-saving measures

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April 2013

Abstract

It is a matter of interest to policy-makers and marketers alike to quantify the impact of environmentally friendly messaging upon consumer decision-making behavior. We quantify the value of such messaging or 'green framing' through a choice experiment where subjects choose technical, home-related energy saving measures (ESMs) after valuing the attributes of a set of alternatives. Green framing is tested through a treatment where the one half of the subject pool is exposed to a scenario description where the energy-savings attribute is formulated as an environmental benefit and the other half a scenario description focussing solely on the economic benefit of the energy-savings attribute. Any significant differences in ESM-attribute valuations are interpreted as caused by green framing. For the experiment we perform a representative online survey among 1084 German residents. Mixed logit analysis reveals that ESM valuations are indeed affected by green framing: financial and environmental descriptions of the energy-savings attribute lead to significantly different attribute valuations, which has obvious marketing and policy implications. We also report statistics on ESM-attribute valuations differentiated by e.g. demographics.

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² Ernst & Young GmbH, Graf-Adolf-Platz 15, 40213 Duesseldorf, Germany, e-mail: gaurav.ghosh@de.ey.com, phone: +49 211 9352 18901.
1 Introduction

In this study, we use a large-scale online choice experiment to analyze consumer valuations of technical energy-saving measures (ESMs) in the house, such as energy-saving light bulbs, triple-glazed windows, and better wall or roof insulation. We are interested in valuing the various attributes of such ESMs like their costs, ease-of-use, and environmental friendliness. The answers to these questions are valuable from both business planning and public policy perspectives. For example, if we find that people are unwilling to pay a premium for environmentally friendly products, but are willing to pay more for products that are recommended by experts, then this implies that advertising strategies that focus on green marketing alone might be misguided and ineffective.

We have designed a choice experiment for ESMs and tested it through pre-tests and discussions with experts and colleagues. Afterwards, we prepared the experiment for final implementation (in German) in cooperation with an experienced market research firm. We have run the survey in April 2012 and now present results, which contribute to the academic literature as well as provide insights for marketing practice. Besides findings on which ESM attributes are valued highest by what type of consumers, we discover that ESM consumers are susceptible to a certain type of framing, i.e., their preferences depend on the formulation of the choice (cf. Tversky and Kahneman, 1981).

Consumer preferences for technical, home-related ESMs were examined recently by means of conjoint choice analysis (e.g., Achtnicht, 2011; Achtnicht and Madlener, 2012; Banfi et al., 2008). These studies assumed rational decision-making, whereas choices about ESMs are complex, where we expect heuristic decision-making (cf. Harmsen – van Hout et al., 2010). In this study, we focus in particular on the possible phenomenon of green framing: we suspect that consumer preferences may be influenced by whether the savings from ESMs are described either as an environmental or as a financial benefit. To the best of our knowledge, this has not been systematically investigated before.

The remainder of this paper is structured as follows. In Section 2, our choice-experimental methodology is explained, and an innovative element in the design to test for green framing described. Section 3 provides mixed logit regression results on which attributes of ESMs are valued highest by what type of consumers, and in how far this is influenced by green framing. In Section 4, we conclude on implications and suggest some further research.
2 Methodology

In our choice experiment, we use abstract names (ESM A, ESM B) rather than specific ESMs like the previous literature. As a consequence, our results are not restricted to specific ESMs, and the identified effects cannot be explained through unobserved consumer preferences for certain ESMs (cf. Achtnicht, 2011, p.2197).

To investigate green framing, we use two different formulations of the energy-savings attribute (randomized between subjects): financial and environmental. Differences in consumer preferences are interpreted as effects of green framing.

We performed a representative online survey among 1084 German residents stratified on age and sex, containing conjoint choice screens like the one illustrated in Table 1. In the real experiment, less extreme attribute values were used instead, and participants only saw either the attribute “savings” in the financial formulation or “greenness” in the environmental formulation.3

Table 1: Illustration of a choice screen

<table>
<thead>
<tr>
<th>Choice situation x</th>
<th>ESM A</th>
<th>ESM B</th>
</tr>
</thead>
<tbody>
<tr>
<td>User effort</td>
<td>Very much</td>
<td>Very little</td>
</tr>
<tr>
<td>Savings / Greenness</td>
<td>1%</td>
<td>90%</td>
</tr>
<tr>
<td>Expert recommendation</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Home comfort</td>
<td>Very low</td>
<td>Very high</td>
</tr>
<tr>
<td>Yearly costs</td>
<td>€1000</td>
<td>€1</td>
</tr>
<tr>
<td>Your choice</td>
<td>A</td>
<td>B</td>
</tr>
</tbody>
</table>

3 Complete instructions in German including a table with descriptions of the attributes and their values are available on request (for further details see also Madlener et al., 2013).
The design was D-optimal\(^4\) and the order in which the attributes were listed to respondents was randomized. Per respondent, our resulting data consist of eight choices among ESMs with varied attributes and 15 background items (demographic characteristics, choice strategies, status quo, etc.).

Our mixed or random parameters logit regression analysis, for which we used Maximum Likelihood estimation with the software NLOGIT 4.0 (Econometric Software, Inc.) and implemented 1000 Halton draws in the Monte Carlo simulations, sheds light on whether consumers are actually affected by green framing, which is relevant for further research since common practice so far assumes rational decision-making. Furthermore, we report on which ESM attributes are valued highest by what type of consumers and when, i.e., under which formulation of the energy-savings attribute, which is relevant for suppliers and policy-makers alike, for a differentiated approach of consumer groups may then be enabled.

3 Results

We restricted our analysis to the 778 respondents who actually accessed any attribute information for all of their choices (for the filtering procedure used see Harmsen – van Hout et al., 2013) to minimize the behavior of systematically choosing ESM A (completely ruled out) and systematically avoiding to choose neither A nor B (some of this behavior remains, as will be shown in the following).

3.1 Baseline regression

Table 2 gives the estimation results and their significance for the baseline regression in which the choice between ESMs is allowed to depend on a heuristic tendency to stick to the status quo and thus choose none of the offered alternatives (no choice), and the attributes “user effort” (effort), “expert recommendation” (expert), “home comfort” (comfort), “yearly costs” (costs), and “financial savings” or “greenness” (savings), respectively.

As can be seen in Table 2, people seem to have a general tendency to avoid the no-choice option and thus to choose any of the two given options whatsoever, which might be due to the hypothetical setting. Furthermore, as intuition predicts, people favor low effort and costs as well as an expert recommendation and high comfort and savings. On average, savings are valued highest, followed by the variables costs, comfort, effort, and expert, consecutively.

\(^4\) Most commonly used in choice experiments, maximizing the determinant of the information matrix of the design.
Table 2: Regression results for baseline regression

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardized coefficient</th>
<th>p-value</th>
<th>Standard dev. distribution</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>no choice</td>
<td>-8.950</td>
<td>0.0000</td>
<td>19.282</td>
<td>0.0000</td>
</tr>
<tr>
<td>effort</td>
<td>-13.136</td>
<td>0.0000</td>
<td>11.308</td>
<td>0.0000</td>
</tr>
<tr>
<td>expert</td>
<td>13.026</td>
<td>0.0000</td>
<td>6.571</td>
<td>0.0000</td>
</tr>
<tr>
<td>comfort</td>
<td>16.028</td>
<td>0.0000</td>
<td>10.625</td>
<td>0.0000</td>
</tr>
<tr>
<td>costs</td>
<td>-17.034</td>
<td>0.0000</td>
<td>16.015</td>
<td>0.0000</td>
</tr>
<tr>
<td>savings</td>
<td>17.751</td>
<td>0.0000</td>
<td>11.106</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

AIC: 1.53599
BIC: 1.54897

3.2 Demographics

Since in the baseline regression we found significant estimated standard deviations of the parameter distributions, we investigated in how far this heterogeneity among consumers can be explained by demographic characteristics. Figure 1 gives an overview of the descriptive statistics (histograms) of the demographic variables known of our (complete) sample. Table 3 gives a summary of the estimation results for separate regressions in which the mentioned demographic variable (excluding possible “not specified” values) is included to explain heterogeneity in mean; any p-value of heterogeneity in mean lower than 0.1 is given in brackets. Full regression results are available from the authors upon request.

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5 This is the distribution of the random parameters, which reflects heterogeneity among respondents.
Figure 1: Histograms for demographic variables

Variables coding in order of appearance: gender (1 = male, 2 = female); age; education (1 = no graduation, 2 = graduation at “Hauptschule”, 3 = graduation at “Realschule”, 4 = “Abitur”, 5 = graduation at “Hochschule”, 6 = not specified); household size (7 = not specified); income (1 = below average, 2 = average, 3 = above average, 4 = not specified); ownership (1 = house owner, 2 = house renter, 3 = not specified).

Table 3: Effects of demographic variables on baseline regression results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>gender</td>
<td>Females have a weaker tendency to avoid the no-choice option (0.0694) and attach more value to expert recommendation (0.0031) than males</td>
</tr>
<tr>
<td>age</td>
<td>The older people are, the stronger their tendency to avoid the no-choice option (0.0035) and the less value they attach to effort (0.0753), expert recommendation (0.0192), and costs (0.0003)</td>
</tr>
<tr>
<td>education</td>
<td>The more highly educated people are, the lower their tendency to avoid the no-choice option (0.0044) and the more value they attach to effort (0.0023), expert recommendation (0.0416), and costs (0.0183)</td>
</tr>
<tr>
<td>household size</td>
<td>There is no difference between valuations of differently sized households</td>
</tr>
<tr>
<td>income</td>
<td>The higher income people have, the less value they attach to costs (0.0032)</td>
</tr>
</tbody>
</table>

6 The German terms can be translated as follows: Hauptschule → lower secondary school; Realschule → intermediate secondary school; Abitur → graduation at higher secondary school (“Gymnasium”); Hochschule → university.
3.3 Green framing

In order to find the effect of green framing on consumer valuations, we repeat the baseline regression, but now include interactions with a dummy variable “green” that equals one for the environmentally geared questionnaire version, and zero for the financially geared one. The results are depicted in Table 4.

As can be seen in Table 4, consumer valuations of ESMs significantly change in three ways as soon as they are given a questionnaire in which the energy-savings attribute is formulated in an environmental rather than a financial way: they attach more value to an expert’s recommendation and also more value to comfort and costs. This shows that green framing does have an impact, and thus should be considered when interpreting results.

Table 4: Regression results with green interactions, reflecting effects of green framing

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardized coefficient</th>
<th>p-value</th>
<th>Standard dev. distribution</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>no choice</td>
<td>-6.680</td>
<td>0.0000</td>
<td>15.084</td>
<td>0.0000</td>
</tr>
<tr>
<td>effort</td>
<td>-10.321</td>
<td>0.0000</td>
<td>6.418</td>
<td>0.0000</td>
</tr>
<tr>
<td>expert</td>
<td>9.155</td>
<td>0.0000</td>
<td>4.851</td>
<td>0.0000</td>
</tr>
<tr>
<td>comfort</td>
<td>11.568</td>
<td>0.0000</td>
<td>7.279</td>
<td>0.0000</td>
</tr>
<tr>
<td>costs</td>
<td>-12.839</td>
<td>0.0000</td>
<td>12.106</td>
<td>0.0000</td>
</tr>
<tr>
<td>savings</td>
<td>15.159</td>
<td>0.0000</td>
<td>8.533</td>
<td>0.0000</td>
</tr>
<tr>
<td>green * no choice</td>
<td>-0.849</td>
<td>0.3960</td>
<td>4.731</td>
<td>0.0000</td>
</tr>
<tr>
<td>green * expert</td>
<td>-1.190</td>
<td>0.2339</td>
<td>6.430</td>
<td>0.0000</td>
</tr>
<tr>
<td>green * comfort</td>
<td>2.305</td>
<td>0.0212</td>
<td>2.530</td>
<td>0.0114</td>
</tr>
<tr>
<td>green * costs</td>
<td>3.190</td>
<td>0.0014</td>
<td>3.982</td>
<td>0.0001</td>
</tr>
<tr>
<td>green * savings</td>
<td>-3.792</td>
<td>0.0001</td>
<td>6.624</td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>-0.772</td>
<td>0.4404</td>
<td>4.086</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

AIC: 1.53208
BIC: 1.55806

If we estimate separate regressions where one of the demographic variables (as illustrated in Figure 1) is included to explain heterogeneity in mean, we find some extra effects of green framing
(only) when focusing on the demographic variable *education* (the respective p-values of heterogeneity in mean are given in brackets): we notice that the more highly educated people are, the lower their tendency to avoid the no-choice option (0.0738) and the more value they attach to effort (0.0701) in the environmentally geared version of the questionnaire.

### 3.4 Robustness

The results described above are among others robust for different ways of coding the costs variable (was effects-coded here), different specifications of the random parameter distributions (were assumed normal here), and attribute order effects (not present). We check for learning effects and, therefore, repeat the baseline regression, but this time include interactions with a dummy variable “experience” that equals zero for the first four choice screens of the respective respondent, and one for the last four screens. The results are reported in Table 5.

**Table 5: Regression results with experience interactions, reflecting learning**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Standardized coefficient</th>
<th>p-value</th>
<th>Standard dev. distribution</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>no choice</td>
<td>-9.486</td>
<td>0.0000</td>
<td>17.774</td>
<td>0.0000</td>
</tr>
<tr>
<td>effort</td>
<td>-10.254</td>
<td>0.0000</td>
<td>9.947</td>
<td>0.0000</td>
</tr>
<tr>
<td>expert</td>
<td>10.265</td>
<td>0.0000</td>
<td>4.986</td>
<td>0.0000</td>
</tr>
<tr>
<td>comfort</td>
<td>12.366</td>
<td>0.0000</td>
<td>9.868</td>
<td>0.0000</td>
</tr>
<tr>
<td>costs</td>
<td>-13.061</td>
<td>0.0000</td>
<td>13.732</td>
<td>0.0000</td>
</tr>
<tr>
<td>savings</td>
<td>13.743</td>
<td>0.0000</td>
<td>9.451</td>
<td>0.0000</td>
</tr>
<tr>
<td>experience * no choice</td>
<td>6.100</td>
<td>0.0000</td>
<td>1.548</td>
<td>0.1216</td>
</tr>
<tr>
<td>experience * effort</td>
<td>-0.855</td>
<td>0.3927</td>
<td>4.236</td>
<td>0.0000</td>
</tr>
<tr>
<td>experience * expert</td>
<td>0.191</td>
<td>0.8486</td>
<td>3.689</td>
<td>0.0002</td>
</tr>
<tr>
<td>experience * comfort</td>
<td>1.416</td>
<td>0.1569</td>
<td>2.171</td>
<td>0.0299</td>
</tr>
<tr>
<td>experience * costs</td>
<td>-3.826</td>
<td>0.0001</td>
<td>2.251</td>
<td>0.0244</td>
</tr>
<tr>
<td>experience * savings</td>
<td>2.149</td>
<td>0.0316</td>
<td>3.788</td>
<td>0.0002</td>
</tr>
</tbody>
</table>

AIC: 1.53141  
BIC: 1.55739

As can be seen in Table 5, over the course of the choice experiment, people significantly learn to decrease their systematic tendency to avoid the no-choice option and to value costs and savings
even higher, where this effect is stronger for costs: costs are second-highest valued by beginners (savings first) and first-highest by experienced participants. Remember that, overall, costs are valued second-highest (cf. Table 2), so the experience effect is not very strong.

Our dataset also contains many other background variables, for which we can in principle perform similar analyses. For some of these, descriptive statistics (histograms) for our complete sample are given in Figure 2.
Figure 2: Histograms for several background variables

Variables coding in order of appearance: interest in energy (1 = not at all, ..., 5 = very much, 6 = not specified); interest in the environment (1 = not at all, ..., 5 = very much, 6 = not specified); status quo effort for energy use (in minutes per week); status quo expert consulted (1 = yes, 2 = no, 3 = not specified); status quo home comfort (1 = very bad, ..., 5 = very good, 6 = not specified); status quo yearly energy costs (in Euros); choice strategy (0 = not specified, {1, ..., 18}: strategy categories, e.g., 10 = savings is important); time used for the choice experiment in seconds; user agent (1 = Mozilla/4.0, 2 = Mozilla/5.0, 3 = Opera/9.8, 4 = Blackberry9700/5.0.0.6561); problems reported (0 = none, {1, ..., 9}: problem categories, e.g., 2 = with covering buttons).
4 Conclusion

This large-scale online choice experiment on consumer preferences for home-related ESMs in Germany found that consumer preferences are affected by green framing in the sense that a financial formulation of the energy-savings attribute leads them to value several attributes differently than in the case of an environmental formulation, which has obvious marketing implications. Furthermore, we elaborately reported on which attributes of ESMs are valued highest by what type of consumers and when (cf. green framing), which is relevant for suppliers and policy-makers alike.

Future work could investigate other types of heuristic decision-making that can be expected in choice-experimental settings. For example, Harmsen - van Hout et al. (2013) find that on average, ESM consumers are not susceptible to a specific bias that may arise from the anchoring-and-adjustment heuristic (Tversky and Kahneman, 1974). Furthermore, Alfnes et al. (2006) show the feasibility of including real incentives in a conjoint choice study on consumer valuations of salmon. However, for practical reasons most conjoint studies are performed without real incentives. It would be possible to find out how critical this is for the results of such a study, say by randomly assigning participants to treatments with and without real incentives in a setting as in Sammer and Wüstenhagen’s (2006) conjoint choice study on the influence of eco-labeling on consumer light bulb choice.

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2010


2009


2008


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