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Authors were provided a format and clear instructions for lay-out. Most authors followed these instructions very good, leading to a consistent presentation of most of the individual papers. Due to the large number of papers, the editors were unable to embark on the time consuming process of adjusting any lay-out errors in papers submitted. Papers had to be reproduced here in the lay-out in which they were submitted, and where authors did - or could - not follow our instructions this may have lead to slight inconsistencies in presentation.

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PART II

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Morning

Chapter 26 Life-cycle cost disclosure, consumer behavior, and business implications

Evidence from an online field experiment[1]

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1 Introduction

A product that looks like a good deal at first glance may turn out to be associated with relatively high costs in the long run. Shoppers face this basic problem when trying to make decisions about energy-consuming durable household appliances.

Can this decision problem be simplified by converting physical energy information (e.g. “kilowatt-hours”) into monetary figures? And do consumers actually change their behavior when being confronted with estimates of appliances’ operating cost and life-cycle cost (i.e. the sum of purchase price and long-run operating cost)?

Prior research has not provided definitive answers in this respect (Anderson and Claxton, 1982; McNeill and Wilkie, 1979); and it was limited with respect to external validity. Another shortcoming is that prior research had nothing to say about the business implications of providing life-cycle cost information to consumers.

This chapter is about a randomized field experiment at a commercially operating online shop that was designed to circumvent some of the limitations encountered in prior research by observing consumer behavior unobtrusively through server log file analysis (Hofacker and Murphy, 2005)

2 Literature review

For more than 20 years, analysts have been wondering why consumers do not invest into more energy-efficient technology at a faster pace. Those investments would be beneficial to consumers because they would reduce

[1] I would like to thank my dissertation committee at the University of Maryland, College Park and, in particular, Matthias Ruth for helpful comments; the German Federal Environmental Foundation (DBU) and the German National Merit Foundation for funding; the team from mentasys, Karlsruhe—Tim Stracke, Michael Krokoska, and especially Philipp Knüchel—for technically implementing the experiment; and quelle.de, Nuremberg for hosting the experimental online shop.

total cost, that is, the sum of purchase price and operating cost. In the literature, the difference between expected and observed consumer behavior has been referred to as the "energy paradox" or the "energy efficiency gap" (Jaffe and Stavins, 1994; Sanstad and Howarth, 1994; Shama, 1983).

2.1 Theoretical background

In the past, the energy efficiency gap has been approached from a rational choice perspective or from a broader behavioral perspective.

The notion of the energy efficiency gap presupposes a rational agent who minimizes all current and expected future costs when buying a durable good. The sum of thoses cost components is known as “life-cycle costs” (LCC) (McMahon et al., 2005, p. 158; Sanstad and Howarth, 1994, p. 812). Life-cycle costing assumes that consumers trade off the present and the future through discounting—be it in implicit or explicit form (Liebermann and Ungar, 2002). The conventional way of discouting involves applying the discounted utility model (Frederick et al., 2002). From a rational choice perspective, one factor that may account for the energy efficiency gap is missing information (Jaffe and Stavins, 1994). From a broader behavioral perspective, the issue goes beyond the mere availability of information. Accordingly, humans are cognitively limited, behave only intendedly rational, and may rely on a range of heuristics for solving problems (Gigerenzer and Selten, 2001; Payne et al., 1993; Simon, 1955). Given humans’ limitations in information-processing, the broader behavioral perspective deems the *form* of information critical, too. In particular, the form of information may be important with respect to energy efficiency labeling on consumer products.

Making intertemporal decisions about products based on energy label information is cognitively demanding because this task represents a complex problem. Some product features are described in physical units, such as kilowatt-hours (for energy), or liters (for water used in washing machines), whereas others, like the product’s price, come in monetary units. Any such multi-critera comparison between products is cognitively demanding, and may involve a trade-off between effort and accuracy in decision-making (Payne et al., 1993). Given consumers’ inclination to reduce their cognitivie effort, they may opt for less-than-optimal products (Häubl and Trifts, 2000; Shugan, 1980) with respect to life-cycle cost. In addition, their choice may depend on the framing of the long-run energy costs, and their coding as losses or gains (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981).

Lastly, the discounted utility model traditionally used for intertemporal allocation problems may, from a behavioral perspective, not describe human decision-making appropriately (Frederick et al., 2002).

In sum, the energy efficiency gap may be partially caused by information problems. From a rational choice perspective, the mere availability of information may matter, whereas from a broader behavioral perspective, the *form* of information may be important, too, for making the decision problem less complex. Such a simplification may be achieved by presenting all *physical* figures which affect operating costs and come in different dimensions in a unified and consistent way: as *monetary* operating costs.

2.2 Monetary operating cost disclosure

The first person to suggest providing monetary operating costs to consumers was Lund (Lund, 1978). He saw life-cycle cost disclosure as a potential “societal instrument” to affect consumers’ shopping decisions in the store. Likewise, the initial US Energy Guide label for household appliances from 1979 carried an estimate of annual monetary operating cost as the centerpiece (US EPA, 1998). With its revision in 1994, however, monetary units did no longer rank prominently on the label. Instead, physical units took their place, and annual operating costs were added only in a smaller font at the bottom (Banerjee and Solomon, 2003). The most recent label revision reversed that change and brought back monetary costs as primary information (Federal Trade Commission, 2007). Likewise, in the European Union—whose own energy efficiency label currently does not show monetary operating cost at all—monetary cost disclosure has been considered recently (EC, 2005, 2006b, 2008). Also, in Europe and abroad, various energy information organizations host websites to provide monetary operating cost and LCC for household appliances to consumers (Bush et al., 2007; Deutsch, 2008; Graulich, 2006).

In view of those discussions and activities, the question is how effective monetary and LCC disclosure actually are. While the idea of simplifying physical information through monetary units has been supported by theoretical reasoning, it has also been actively demanded by consumers (du Pont, 1998; Thorne and Egan, 2002). Similarly, ethnographic research on “folk units” of measurement has shown that consumers prefer monetary figures over physical figures when analyzing their energy use at home (Kempton and Montgomery, 1982).

Despite the potential advantages of monetary cost disclosure over physical information disclosure, it has not attracted as much attention as other aspects of labeling (Banerjee and Solomon, 2003; Gallastegui, 2002); and it has rarely been evaluated in a rigorous way.

2.3 Evaluations of monetary cost and life-cycle cost disclosure

While the focus of energy label evaluations has often been on studying awareness and understanding (Dyer and Maronick, 1988; Federal Trade Commission, 2006; Rubik and Frankl, 2005), only few researchers have investigated labels’ effects on consumer behavior experimentally (Bjorner et al., 2004; Sammer and Wüstenhagen, 2006). In particular, experiments that compare the effects on consumer behavior of physical energy information versus monetary information are hard to find.

Three related journal articles stem from the early 1980s (Anderson and Claxton, 1982; Hutton and Wilkie, 1980; McNeill and Wilkie, 1979). All of them focused on the mean specific energy use of the products chosen by consumer as the dependent variable. As independent variables, the studies varied the format in which energy information was provided to consumers (see Deutsch 2008 for a more detailed comparison).

In two of the three studies, no significant difference ($p<0.05$) could be found between the effect on consumer behavior of physical energy information and monetary information (Anderson and Claxton, 1982; McNeill and Wilkie, 1979). In one of them, consumers who received life-cycle cost estimates chose products with less specific energy use, relative to a control group that was provided with yearly operating cost (Hutton and Wilkie, 1980).

Two of the three studies are methodologically limited in that they were not conducted in the field. They lacked tangible financial incentives that may have encouraged participants to concentrate on costs more strongly. Moreover, the pool of participants was restricted to females. At least the third study was performed in the field, but here, the researchers encountered implementation problems (Anderson and Claxton, 1982).

Overall, our knowledge about the causal effect on consumer behavior of monetary energy cost disclosure in general, and life-cycle cost disclosure in particular, is limited.

3 Experimental online shop

3.1 Hypotheses

Given the literature review, I proposed that life-cycle cost disclosure would influence consumer behavior with respect to the choice of washing machines. My three null hypotheses referred to the appliances' specific energy and water use, life-cycle cost, the number of click-throughs, and product prices.

H_{01}: *"The disclosure of life-cycle cost does not make online shoppers opt for washing machines that are different in terms of their specific energy use."*

Analogously, a similar null hypothesis (H_{02}) referred to the potential change in specific water use of the chosen appliances.

Given ambiguous prior research findings regarding decision-support systems in general (Sharda et al., 1988) and life-cycle cost disclosure in particular (as described above), I utilized nondirectional hypotheses.

I also examined whether the experimental treatment would change the estimated life-cycle cost associated with the chosen appliances:

H_{03}: *"The disclosure of life-cycle cost does not make online shoppers opt for washing machines that are different in terms of their estimated life-cycle cost."*

As to the economic impact for the website, the online shop's turnover depends on the quantities and prices of washing machines sold.

H_{04}: *"The disclosure of life-cycle cost does not change the number of products put into the virtual shopping cart."*

Similarly, the treatment may have an effect on the price of products chosen.

H_{05}: *"The disclosure of life-cycle cost does not change the price of products put into the virtual shopping cart."*

As before, the hypotheses were nondirectional. On the one hand, treated consumers may have perceived life-cycle cost disclosure as a helpful feature. On the other hand, they may have disliked the fact that life-cycle cost disclosure increases the overall information load and makes the website more cognitively demanding (Chiang et al., 2005).

3.2 Site description

The experimental data was gathered from *Quelle*, a major German mail-order business which operates an online shop at www.quelle.de with up to nine million website "visits" per month (Quelle, 2006). Quelle offers a wide range of products including household appliances. For washing machines, the online shop offers a specialized recommendation agent that is operated by Mentasys, an independent Germany-based software company. Mentasys' recommendation agent asks consumers about their preferences, and ranks all washing machines according to these criteria. Consumers can drop/add machines, change their preferences, and compare all available washing machines with each other in detail. The energy efficiency information used by the recommendation agent is consistent with the requirements of the EU appliance labeling directive (EC, 1995, 1996).

The recommendation agent is accessible in two distinct recommendation modes—*Simple Search* and *Expert Search*. The two modes differ regarding the scope of initial preference elicitation, and with respect to the visual presentation of recommended washing machines.

3.3 Design and treatment

In this two-group posttest-only randomized experiment with cross-sectional data from different internet users, the control group saw regular product price information at all times, whereas the treatment group also saw estimated operating and life-cycle cost.

3.3.1 Display and calculation of life-cycle cost

The treatment group received information for each product in the following format:

Life-cycle cost = purchase price + operating cost

Despite certain visual differences between the two recommendation modes Simple Search and Expert Search, the presentation of life-cycle cost in the respective treatment groups was basically the same. Table 1 on the next page shows the experimental conditions in the Simple Search mode.

Life-cycle costs (LCC) were estimated as follows:

$$LCC = P + \sum_{t=1}^{N} \frac{C_t}{(1+r)^t}$$

where P = appliance purchase price [€], C_t = yearly operating cost [€/year],

N = chosen time horizon [years], and r = discount rate.

For discontinuously working washing machines, operating costs were calculated as

$$C_t = (P_E * C_E + P_W * C_W) * m * k$$

where P_E = price of electricity [€/kWh], C_E = specific consumption of energy [kWh/cycle], P_W = price of water [€/m^3], C_W = specific consumption of water [m^3/cycle], m = number of cycles per week [cycles/week], and k = 52 [weeks/year]. Both C_E and C_W are based on standard 60°C cotton cycles as defined in the European Commission's labeling directive for washing machines (EC, 1995).

This simplification disregards shipping cost, installation cost, maintenance cost, and cost for detergents, which is consistent with the kind of information presented by most other energy websites for consumers (Deutsch, 2008).

Table 1: Conditions in the Simple Search mode of the online shop

<table>
<tr><th>Experimental condition</th><th>Visual stimuli for sample washing machine</th></tr>
<tr><td>Control

with

regular price information</td><td>
</td></tr>
<tr><td>Treatment

with

additional operating cost and life-cycle cost estimates</td><td>
</td></tr>
</table>

Note: In each experimental condition, the first line contains the appliance model, and the second line a short product characterization. The following paragraph describes product features such as energy efficiency class, maximum spin speed, washing performance class, loading capacity, and additional washing program information. The third paragraph shows price information; the fourth paragraph (only in the treatment group) shows time horizon, life-cycle cost, price and operating cost. Operating cost can be adjusted by clicking on "geschätzte Betriebskosten". Via the links in the penultimate line, one can receive more detailed product information, or put the appliance into the virtual shopping cart, respectively.

3.3.2 *Usage assumptions and their adjustment*

Users in the treatment group could choose to adjust the assumptions necessary for LCC estimation. For the purpose of discounting future operating costs, I tested *direct* and *indirect* discounting procedures, and I eventually applied the latter throughout the experiment.

Potentially, direct discounting could have been realized by asking users explicitly about their individual discount rates, or by offering them “price tasks” , “matching tasks”, “choice tasks”, or “rating tasks” (Frederick et al., 2002).

Since a pre-test of the first option revealed that users did not comprehend such form of direct discounting, it was substituted for by *indirect discounting*.

Indirect discounting as understood in the context of this project implies that undiscounted operating costs can be reduced through a calculatory shortening of the underlying time horizon. Indirect discounting has the same effect as conventional direct discounting: both reduce the estimated initial operating costs. Of course, the real physical lifetime of a given appliance may differ from the time horizon discussed here. The reference time horizon used for indirect discounting simply determines the relative cost-effectiveness of an appliance vis-à-vis other appliances. In this fashion, direct discounting can be functionally replaced by an *equivalent time horizon* (see appendix for a derivation).

With indirect discounting, the overall equation for life-cycle cost is, therefore, given as:

$$LCC = P + ETH * (P_E * C_E + P_W * C_W) * m * k$$

where P = appliance purchase price [€], ETH = equivalent time horizon [years], P_E = price of electricity [€/kWh], C_E = specific consumption of energy [kWh/cycle], P_W = price of water [€/m^3], C_W = specific consumption of water [m^3/cycle], m = number of cycles per week [cycles/week], and k = 52 [weeks/year].

When starting the recommendation agent, users would see operating costs estimated on the basis of a set of default assumptions regarding discount rate, time horizon, prices and behavioral parameters (see Table 2). Subsequently, they were able to adjust the discount rate indirectly by changing the underlying time horizon.

Table 2: Default assumptions for estimating operating costs

Default assumption	Default value	Unit	Reference year	Comment (Reference)
Price of electricity	0.16	€/kWh	2005	Mean value for Germany (VDEW, 2005)
Price of water	3.95	€/m3	2003;2005	Mean value for Germany; sum of drinking water price (BGW, 2005b) and waste water price (BGW, 2005a)
Service life	12.7	years	2004	Mean values for Germany from representative survey (GfK, 2006)
Frequency of use	3	cycles/	2002	Rounded to integer (derived from 12.2 times per month) (Schlomann et al., 2004, p. 72)
Equivalent time horizon	9	week	2006	Based on an implicit discount rate of about 6% and service life of 12.7 years; see appendix for derivation

3.4 Procedure

To keep the experimental conditions as realistic as possible, I gathered the data without obtaining participants' informed consent prior to participation.[2]

Consumers arrived at the homepage of the online shop and started the recommendation agent, which offered them a choice between the two alternative recommendation modes Simple Search and Expert Search. In the Simple Search mode, the subsequent preference elicitation consisted of five different questions, while in the Expert Search mode, users could specify up to 12 preferences. Both modes covered questions regarding the general sort of the sought-after washing machine, its price range, the size of the user's household, the likely location where the appliance would be used, and the preferred manufacturer.

Random assignment occurred before users could see the agent's washing machine recommendations for the first time. Technically, the experimental groups were separated via cookies. Operating and life-cycle cost for the treatment group were estimated based on default usage assumptions as listed in table 2.

Regardless of the chosen recommendation mode, users in the treatment group could adjust the underlying assumptions for the calculation of operating costs (see figure 1 in appendix I). Furthermore, both experimental groups could choose to see an in-depth comparison in matrix format with detailed product characteristics.

3.5 Data collection and preparation

During the year 2006[3], Mentasys collected click-stream data for washing machines from the server log files of the recommendation agent.

Mentasys identified and removed hits from non-human user agents by means of blacklists for Internet Protocol addresses and user-agent information, and delivered the resulting log files.

Two sorts of problematic clicks in the log files made me further prepare the data prior to the main analysis. First, repeated clicks by the same user on exactly the same appliance appeared to be a product of impatient clicking behavior. In such cases, I kept only the first click in the sample. Second, a user with a total of 20 click-throughs or more looked suspicious to me, and was considered to be a non-human user agent. Such behavior was observed for nine users, and their observations were dropped entirely. Overall, I discarded 2123 clicks so that 2065 click-throughs remained.

3.6 Measures

The dependent and independent variables used in this experiment refer to products that users put into the virtual shopping cart ("click-throughs").

Dependent variables encompassed specific energy and water consumption per standard washing cycle, as well as the total number of clicks, product price, and life-cycle cost. Since life-cycle cost by definition

[2] This procedure had been approved by the Institutional Review Board of the University mentioned in the acknowledgements.

[3] Due to proprietary information concerns, the exact period of time cannot be disclosed here.

was not shown to users in the control group, these users had to be assigned life-cycle cost estimates derived from common default assumptions about price and time horizon (see table 2). All dependent variables of interest are shown in table 3.

Table 3: Key dependent variables

Dependent variable	Meaning / Comment
energy	Specific energy use of appliance [kWh/standard cycle]
water	Specific water use of appliance [m^3/standard cycle]
lccost	Estimated life-cycle cost of appliance [€], simulated for control group based on default assumptions
ct count	Count of click-throughs per user
price	Price of appliance [Euro]

The independent variables included the capacity [in liters], and dummy variable sets for energy efficiency class [A++, A+, A to F], brand, and merchant of a given appliance.

For coping with potential bias resulting from unidentified clicks by non-human user agents, I checked how robust the results for energy use were. Not only did I analyze *all* click-throughs, but I also scrutinized the smaller subset of each user's *final* click-through. By using each one's final click-through, no individual user could affect the estimates more strongly than any other user.

3.7 Models

I employed the following regression model for testing hypothesis H_{01} that the energy-efficiency of chosen products is unrelated to the treatment:

$$energy_i = \beta_0 + \beta_1\, treatment_i + \beta_2\, Z_i + u_i$$

where *energy* = specific energy use [kWh/cycle] for washing machine *i*, *treatment* = treatment dummy variable, *Z* = vector of covariates, and *u* = error term. This basic model was estimated separately for each of the two recommendation modes. Moreover, I also used a logarithmic specification:

$$ln(energy)_i = \beta_0 + \beta_1\, treatment_i + \beta_2\, Z_i + u_i$$

Similar models were estimated for specific water use, estimated life-cycle cost, and appliance prices as dependent variables. I added several covariates to the models (Neter and Wasserman, 1974; Stock and Watson, 2003), and I estimated all models with ordinary least squares.

For testing the hypothesis H_{04} that the treatment does not affect online shoppers' number of click-throughs to put products into the virtual shopping cart, I employed a negative binomial regression model of the following form:

$$ctcount_i = \beta_0 + \beta_1\, treatment_i + \beta_2\, Z_i + u_i$$

where *ctcount* = number of click-throughs per user *i*, *treatment* = treatment dummy variable, *Z* = vector of covariates, and *u* = error term.

3.8 Results

In sum, the online shop was visited by about 95000 separately identifiable users. In both recommendation modes, they were shown more than 160 different appliances from 7 different brands. In what follows, I refer to the combined total of 2065 products that users put into the virtual shopping cart.

3.8.1 Overall energy use, water use, and life-cycle costs

Both mean and median specific energy use are lower in the treatment group than in the control group (table 4). The same is true for water use (table 5). Mean life-cycle cost is also lower in the treatment group, while median life-cycle cost are the same as in the control group (table 6).

Table 4: Descriptive statistics for overall specific energy use

All click-throughs	N	Mean energy	Median energy	SD energy	Min. energy	Max. energy
Control	1040	0.975	1.02	0.118	0.57	1.36
Treatment	1025	0.962	0.95	0.115	0.57	1.36
Total	2065	0.969	0.95	0.116	0.57	1.36

Note: Energy in [kWh/cycle].

Table 5: Descriptive statistics for overall specific water use

All click-throughs	N	Mean water	Median water	SD water	Min. water	Max. water
Control	1040	44.30	44	5.0	34	60
Treatment	1025	43.81	42	4.9	34	60
Total	2065	44.06	42	5.0	34	60

Note: Water in [L/cycle]

Table 6: Descriptive statistics for overall life-cycle cost

All click-throughs	N	Mean lccost	Median lccost	SD lccost	Min. lccost	Max. lccost
Control	1040	953.3	901	134	798	1650
Treatment	1025	952.6	901	151	549	2043
Total	2065	953.0	901	143	549	2043

Note: Life-cycle cost in [Euro]. Life-cycle costs were only shown to the treatment group and were therefore simulated for the control group based on default assumptions.

Table 7 shows that the treatment affects both specific energy and water use when controlling for other factors. It reduces energy use by 0.77% (model 2) to 0.83% (model 3). These results are significant at a 1% level. The treatment also reduces water use by 0.74% (p<0.05), but it has no significant effect on estimated life-cycle cost.

Table 7: Effect on overall specific energy use, water use and life-cycle cost

	ln(energy)				ln(water)	ln(lccost)
	(1) All CT	(2) All CT	(3) All CT	(4) Final CT	(5) All CT	(6) All CT
treatment	-0.014*	-0.0077**	-0.0083***	-0.0083**	-0.0074*	0.00031
	(0.0053)	(0.0026)	(0.0021)	(0.0026)	(0.0034)	(0.0043)
ln(capacity)		0.86***	0.95***	0.96***	0.73***	0.48***
		(0.0090)	(0.0095)	(0.014)	(0.020)	(0.026)
mode			-0.0024	-0.0041	-0.034***	0.034***
			(0.0023)	(0.0028)	(0.0036)	(0.0046)
constant	-0.032***	-1.49***	-1.49***	-1.76***	2.92***	6.65***
	(0.0038)	(0.016)	(0.0081)	(0.039)	(0.023)	(0.044)
efficiency class	No	No	Yes	Yes	Yes	Yes
brands	No	No	Yes	Yes	Yes	Yes
other features	No	No	Yes	Yes	Yes	Yes
adj. R-sq	0.003	0.762	0.840	0.846	0.537	0.459
N	2065	2065	2065	1437	2065	2065

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001,
CT: Click-through to put appliance into virtual shopping cart. mode: recommendation mode (Simple search, Expert search). Model 4 contains only final CTs and serves as a robustness check for models 1 to 3.

3.8.2 Overall impact on retail volume

Turnover depends on prices and the number of click-throughs. The sum of prices is higher in the control group, while the mean price is higher in the treatment group (table 8). The mean number of click-throughs is lower in the treatment group (table 9).

Table 8: Descriptive statistics for appliance prices

All click-throughs	N	Sum price	Mean price	SD price	Min. price	Max. price
Control	1040	508091	488.5	132	299	1160
Treatment	1025	500772	488.6	129	299	1160
Total	2065	1008863	488.6	131	299	1160

Note: Prices in [Euros]

Table 9: Descriptive statistics for number of clicks per user

All click-throughs	N users	Mean CT count	Median CT count	SD CT count	Min. CT count	Max. CT count
Control	47665	0.022	0	0.22	0	15
Treatment	47692	0.021	0	0.23	0	16
Total	95357	0.022	0	0.22	0	16

Note: CT: click-through to put appliance into virtual shopping cart

The tables below contain regression results for prices (table 10) and the number of click-throughs (table 11). When controlling for other factors, the treatment does not have an effect on prices nor click-throughs at a 5% level of significance.

Table 10: Effect on appliance prices

	ln(price)		
	(1)	(2)	(3)
	Simple search	Expert search	Overall
treatment	-0.0041	-0.0093	0.00037
	(0.0095)	(0.013)	(0.0092)
ln(capacity)	0.11*	-0.085	0.22***
	(0.054)	(0.068)	(0.053)
mode			0.074***
			(0.0096)
constant	6.40***	6.56***	6.88***
	(0.12)	(0.096)	(0.057)
efficiency class	Yes	Yes	Yes
brands	Yes	Yes	Yes
other features	Yes	Yes	Yes
preferences	Yes	No	No
adj. R-sq	0.626	0.171	0.212
N	990	1075	2065

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, mode: recommendation mode (Simple search, Expert search). User preferences were logged only in the Simple search mode.

Table 11: Effect on the overall number of click-throughs

	Count of click-throughs per user
treatment	-0.020
	(0.060)
mode	0.95***
	(0.062)
constant	-7.47***
	(0.16)
lnalpha	
constant	2.14***
	(0.056)
browsers	Yes
pseudo R-sq	0.237
N	95357

Note: Standard errors of the negative binomial regression in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$, mode: recommendation mode (Simple search, Expert search).

As a final point, I also investigated how sensitive the treatment effect was with respect to changes in perceived energy prices by adding the then current price of regular gas in Germany as a covariate. Alternative specifications included the price of gas in time-lagged form. Since such modifications, however, did not change the experimental results noticeably, if at all, those coefficient estimates are not reported explicitly here.[4]

3.9 Discussion

3.9.1 Experimental outcomes

The negative estimates for the effect on specific energy use are significant at a 1% level. Substantively, however, they are much smaller (-0.83%) than what has been reported by Hutton and Wilkie (1980), who found effects ranging from -12% to -27%. But when taking into account differences in experimental settings, labeling systems and energy prices, both findings still consistently suggest that life-cycle cost disclosure affects consumers' choices towards products with higher energy efficiency. The same seems to be true with respect to specific water use, which also gets reduced by the treatment.

Estimated life-cycle costs, on the other hand, are not affected by the treatment. Since life-cycle costs were—by definition—not disclosed to the

[4] Another variant of the experiment encompassed a different presentation of operating costs and LCC. In that variant, long-run costs were presented in a more prominent way. Moreover, the default time horizon amounted to only about five years, which is equivalent of saying that the assumed implicit discount rate was higher. While I could not detect a significant ($p<0.05$) treatment effect on specific energy use in that variant, the effect size for water use was about the same (-0.72%) as the effect size reported in the experiment at hand. More detailed results can be obtained from the author.

control group, they had to be simulated for comparing life-cycle cost between treatment and control. This simulation for the control group was based on common default assumptions (see table 2). Life-cycle cost estimates for the treatment group, on the other hand, were derived from user-adjusted assumptions. Therefore, in the treatment group, the underlying assumptions deviated from the default assumptions. But even after balancing this asymmetry and comparing non-adjusted default assumptions for both experimental groups, none of the treatment coefficients would have been significant at a 5% level.

Given the online shop's business model, the number of click-throughs and the prices of clicked appliances jointly matter for turnover. Since the product of click-throughs and appliance prices—that is, the best available indicator of turnover—is lower in the treatment group, this finding suggests the possibility of a negative impact on retail volume. When controlling for other factors, however, the treatment does not have an effect on prices nor click-throughs at a 5% level of significance. In any case, both a neutral or negative effect on turnover constitutes a barrier for private firms to embrace life-cycle cost disclosure.

3.9.2 Internal validity

When checking regression residuals, in most cases, I had to reject the hypothesis of normally distributed error terms. Yet, in sufficiently large sample sizes, regression coefficients can be assumed to be robust against such a violation (Bohrnstedt and Carter, 1971).

Internal validity would also be threatened if the treatment and control group were incomparable. I checked their comparability by verifying the success of random assignment (Stock and Watson, 2003). Gauged by the distribution of browser and operating system information across groups (Peterson, 2004), randomization worked correctly. I also looked at the acceptance of cookies, which were needed for separating the experimental groups. For persistent cookies, the acceptance rate was always higher than 90%. Still, high acceptance rates may be misleading because users may choose to erase their cookies by themselves more or less regularly. Such behavior has been reported for a considerable share of German internet users (van Eimeren et al., 2004). Accordingly, in 2004, 37% of them deleted their cookies at the end of a given session, and 42% deleted them at least once a week. But even if all users accepted persistent cookies forever, users would still be able to enter the respective other experimental group by accessing the online shop from a different computer (Reips, 2002).

A possible result from uncontrollable change in experimental conditions is bias. Being in the treatment group first, and entering the control group thereafter may entail priming effects (Mandel and Johnson, 2002). After seeing life-cycle cost once, a user would probably focus more intensely on energy cost information, and he would tend to opt for relatively more energy-efficient appliances. As a consequence, the mean difference measured between control and treatment group would diminish—i.e. such effect would introduce a conservative bias.

It is much harder to think of an opposite effect with an upward bias. Theoretically, users could have been assigned to the treatment group first, and to the control group thereafter, and they may have clicked on less efficient appliances after the change in experimental conditions. Such a scenario, however, seems to be rather hypothetical. Given the field character of the experiment, consumers were facing an actual purchase situation associated with real budget constraints. Therefore, they were unlikely to make themselves deliberately worse off by choosing less efficient appliances, even though an unexpected change in experimental conditions may have been somewhat confusing to them.

In sum, the threats to internal validity described above may have led to a bias, which, in all likelihood, would have underestimated the treatment effect of life-cycle cost disclosure on consumer behavior.

3.9.3 External validity

First, the treatment effect may have varied with time. Interfering events such as increases or decreases in energy prices may have had an impact on it. I tested this hypothesis by including the price of gas—a readily available indicator that consumers can be assumed to know well—into my regression models.Given the non-significance of this variable, however, the treatment seems to have been relatively stable over time.

Second, it is impossible to say if the users visiting the experimental online shop differed from the larger population of users, for example, with respect to their interest in matters of energy-efficiency (Reips, 2002).

Third, the washing machines offered in the online shop represent only a limited subset of all products and brands available in the market. Therefore, a generalization of the experimental findings to the whole product range in the market seems to be limited. The larger the range of products with respect to energy use, the greater a treatment effect could potentially be. Given the online shop's restricted range of products, the most likely bias would reduce the treatment effect size.

Finally, the experimental recommendation agent was only one of two alternative ways to buy a washing machine in the online shop. Users who navigated through the regular online shop interface were not included in the sample. Given different information needs and search behavior, and given the existing variance in users' ability to cope with hierarchical menu structures (Norman, 1991), the direction of any potentially resulting bias is unknown.

3.9.4 Measurement validity

Washing machines are used discontinuously with a variety of programs at varying temperatures. This diversity in usage, however, could not be reflected in the experimental design given a lack of appropriate data. Instead, the values for specific energy and water use refer to standard 60°C cotton cycles as defined in the European Commission's labeling directive for washing machines (EC, 1995). Any treatment effect reported here must therefore be interpreted as an average change in specific, standardized appliance characteristics. Actual energy use or water use may be different and depends on individual consumer behavior.

Threats to measurement validity comprise double clicks and clicks from non-human user agents. I handled these threats by comparing two sorts of results: those from regressions that included *all* observations, and those that included only each user's *final* click-through. The comparison shows that the treatment effect on energy use was very similar in both variants. Any potentially remaining measurement bias, therefore, must be relatively small.

Finally, the instruments described here are products which users had put into the virtual shopping cart. Although they refer to real consumer behavior, they cannot answer the ultimate question whether a given consumer actually bought the product in the shopping cart. Since the online shop's software systems were not further integrated, however, I was not able to gather data on final purchases.

4 Overall conclusion

Disclosing estimated life-cycle costs to shoppers makes them opt for washing machines with, on average, 0.83% less specific energy consumption and 0.74% less specific water consumption. Therefore, life-cycle cost disclosure may have some potential for environmental policy. On the other hand, it seems not to increase the online shop's retail volume, which makes in unattractive from a pure business perspective.

But it remains an open question for future research whether monetary energy cost disclosure in another *format* would have more positive business implications. Alternative formats encompass, for example, annualized life-cycle costs (Graulich, 2006), and a different framing of information as long-run *savings* (rather than *additional costs*) relative to a reference appliance (Alexandru et al., 2006; EC, 2006a). Lastly, internal validity could be strengthened by conducting research that measures actual final purchases; and external validity could be increased by performing similar research for different countries with other energy prices.

Appendix I: Adjustment of assumptions

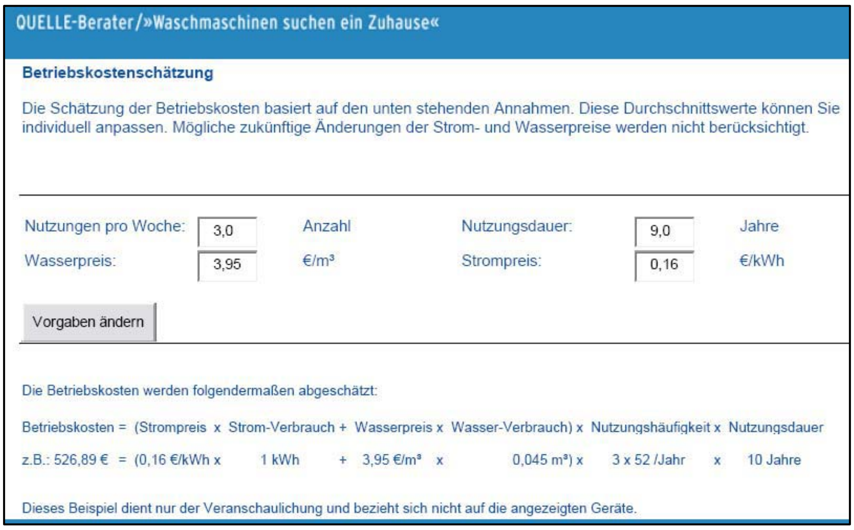

Figure 1: Adjustment of assumptions in the treatment group

Note: The first paragraph clarifies that the estimation relies on adjustable assumptions (shown in the second paragraph), and that the default assumptions are average values. It also cautions that potential future changes in electricity and water prices are not reflected in this static estimation of operating costs. The last three paragraphs present a sample estimation of operating costs and make explicitly clear that the sample estimation does not refer to any particular appliance currently looked at by the consumer.

Appendix II: Equivalent time horizon and default assumptions

The default discount rate chosen for this experiment was about 6%, close to the then-current long-term interest rate of about 4% (Deutsche Bundesbank, 2006). The yardstick was a rational agent who tries to make beneficial investments and whose implied discount rate can be expected to converge on the market interest rate. Since consumers may consider the investment into a washing machine as somewhat risky (Frederick et al., 2002; Sutherland, 1991), the remaining difference between 4% and 6% was supposed to cover this risk premium.

Based on the default discount rate, the equivalent time horizon (ETH) was derived as follows. Fundamentally, operatings costs calculated with an ETH must be the same as those computed through conventional discounting, which yields the general condition:

$$\sum_{t=1}^{T} C_t (1+r)^{-t} \overset{!}{=} \sum_{t=1}^{ETH} C_t$$

where C_t = annual operating cost in year t, T = the known average service life of a given household appliance, r = discount rate, ETH = equivalent time horizon. For constant C_t (as assumed here), the expression can be reduced to

$$\sum_{t=1}^{T} (1+r)^{-t} \overset{!}{=} \sum_{t=1}^{ETH} \quad = ETH$$

Given a known average service life of 12.7 years for washing machines, and an implicit discount rate of 6%, the ETH amounts to about 9 years. Those 9 years were used as default values throughout the experiment. Users could adjust the ETH according to their preferences; and when doing so, they implicitly adjusted the underlying discount rate. Still, they were never explicitly told about the notion of discounting.

Incorporating indirect discounting and the ETH into the life-cycle cost concept yields:

$$LCC = P + ETH * (P_E * C_E + P_W * C_W) * m * k$$

where P = appliance purchase price [€], ETH = equivalent time horizon [years], P_E = price of electricity [€/kWh], C_E = specific consumption of energy [kWh/cycle], P_W = price of water [€/m^3], C_W = specific consumption of water [m^3/cycle], m = number of cycles per week [cycles/week], and k = 52 [weeks/year].

References

Alexandru, A., Caponio, R., Jitaro, E., Jofra, M., Krivosik, J., Turan, S., et al. (2006, 21-23 June). *Informing and educating students and their families about energy efficient appliances*. Paper presented at the EEDAL'06: International Energy Efficiency in Domestic Appliances & Lighting Conference '06, London.

Anderson, C. D., and Claxton, J. D. (1982). *Barriers to Consumer Choice of Energy Efficient Products*. Journal of Consumer Research, 9(2), 163.

Banerjee, A., and Solomon, B. D. (2003). *Eco-labeling for energy efficiency and sustainability: a meta-evaluation of US programs.* Energy Policy, 31(2), 109-123.

BGW. (2005a). *Abwasserstatistik 2003*. Berlin: Bundesverband der deutschen Gas- und Wasserwirtschaft (BGW)

BGW. (2005b). *Kurz notiert: Trinkswasserpreise*. Berlin: Bundesverband der deutschen Gas- und Wasserwirtschaft (BGW)

Bjorner, T. B., Hansen, L. G., and Russell, C. S. (2004). *Environmental Labeling and Consumers' Choice--An Empirical Analysis of the Effect of the Nordic Swan.* Journal of Environmental Economics and Management, 47(3), 411.

Bohrnstedt, G. W., and Carter, T. M. (1971). *Robustness in Regression Analysis*. Sociological Methodology, 3, 118-146.

Bush, E., Attali, S., Brunner, C. U., and Niederberger, A. A. (2007, 4-9 June 2007). *Topten – Best of Europe. How do best products perform and why aren't they sold across Europe?* Paper presented at the ECEEE 2007 Summer Study

Chiang, K.-P., Dholakia, R. R., and Westin, S. (2005). *e-search: a conceptual framework of online consumer behavior*. In Y. Gao (Ed.), Web systems design and online consumer behavior (pp. 1-18). Hershey, PA: Idea Group Pub.

Deutsch, M. (2008). *Life-Cycle Cost Disclosure and Consumer Behavior: Expectations in the Energy Policy Community Versus Experimental Evidence.* In D. M. Bergmann (Ed.), Energy Efficiency Research Advances. Hauppauge, NY: Nova Science Publishers.

Deutsche Bundesbank. (2006, 1 December 2006). *Zeitreihe wz3414: Aus der Zinsstruktur abgeleitete Renditen für Bundeswertpapiere mit jährl. Kuponzahlungen / RLZ 15 Jahre / Monatsendstand*. Retrieved December 6, 2006, from http://www.bundesbank.de/statistik/statistik_zeitreihen.php?func=row&tr=wz3414

du Pont, P. (1998). *Energy policy and consumer reality: The role of energy in the purchase of household appliances in the United States and Thailand.* Unpublished dissertation, University of Delaware, Newark.

Dyer, R. F., and Maronick, T. J. (1988). *An Evaluation of Consumer Awareness and Use of Energy Labels in the Purchase of Major Appliances: A Longitudinal Analysis*. Journal of Public Policy & Marketing, 7(1), 83-97.

EC. (1995). *Commission Directive 95/12/EC of 23 May 1995 implementing Council Directive 92/75/EEC with regard to energy labelling of household washing machines.*

EC. (1996). *Commission Directive 96/89/EC of 17 December 1996 amending Directive 95/12/EC implementing Council Directive 92/75/EEC with regard to energy labelling of household washing machines*.

EC. (2005). *Doing more with less.* Green Paper on energy efficiency (No. COM(2005) 265). Brussels: European Commission.

EC. (2006a). *European Appliance Information System.* Retrieved 11 July, 2006, from http://www.eais.info

EC. (2006b). *Report on the Analysis of the Debate of the Green Paper on Energy Efficiency. Commission Staff Working Document* (No. SEC(2006) 693). Brussels: European Commission.

EC. (2008). *Consultation document on the revision of the Energy Labelling Directive 92/75/EEC of 22 September 1992 on the indication by labelling and standard product information of the consumption of energy and other resources by household appliances* Brussels: European Commission.

Federal Trade Commission. (2006). *Agency Information Collection Activities*; Comment Request. Federal Register, 71(121), 36088-36096.

Federal Trade Commission. (2007). *Rule Concerning Disclosures Regarding Energy Consumption and Water Use of Certain Home Appliances and other Products Required Under the Energy Policy and Conservation Act (''Appliance Labeling Rule'')*; Final Rule. Federal Register, 72(167), 49948-49997.

Frederick, S., Loewenstein, G., and O'Donoghue, T. (2002). *Time Discounting and Time Preference: A Critical Review*. Journal of Economic Literature, 40(2), 351-401.

Gallastegui, I. G. (2002). *The use of eco-labels: a review of the literature*. European Environment, 12(6), 316-331.

GfK. (2006). *Mean useful life in years of the previous appliance. GfK Electro*Scope 2004*. Personal Communication with Hans-Ulrich Finck as of 2006-01-13. Nürnberg: Gesellschaft für Konsumforschung.

Gigerenzer, G., and Selten, R. (2001). *Rethinking Rationality*. In G. Gigerenzer & R. Selten (Eds.), Bounded rationality : the adaptive toolbox (pp. 1-12). Cambridge, Mass.: MIT Press.

Graulich, K. (2006, 21-23 June). *EcoTopTen - Innovations for Sustainable Consumption*. Paper presented at the EEDAL'06: International Energy Efficiency in Domestic Appliances & Lighting Conference '06, London.
Häubl, G., and Trifts, V. (2000). *Consumer decision making in online shopping environments: The effects of interactive decision aids*. Marketing Science, 19(1), 4.
Hofacker, C. F., and Murphy, J. (2005). *Using Server Log Files and Online Experiments to Enhance Internet Marketing*. In S. Krishnamurthy (Ed.), Contemporary research in e-marketing (Vol. 1, pp. 226-249). Hershey, PA: Idea Group Pub.
Hutton, R. B., and Wilkie, W. L. (1980). *Life Cycle Cost: A New Form of Consumer Information*. Journal of Consumer Research, 6(4), 349-360.
Jaffe, A. B., and Stavins, R. N. (1994). *The energy-efficiency gap. What does it mean?* Energy Policy, 22(10), 804-810.
Kahneman, D., and Tversky, A. (1979). *Prospect Theory: An Analysis of Decision under Risk*. Econometrica, 47(2), 263-292.
Kempton, W., and Montgomery, L. (1982). *Folk quantification of energy*. Energy, 7(10), 817-827.
Liebermann, Y., and Ungar, M. (2002). *Efficiency of consumer intertemporal choice under life cycle cost conditions*. Journal of Economic Psychology, 23(6), 729-748.
Lund, R. T. (1978). *Life-cycle costing: A business and societal instrument*. Management Review, 67(4), 17.
Mandel, N., and Johnson, E. J. (2002). *When web pages influence choice: effects of visual primes on experts and novices*. Journal of Consumer Research, 29(2), 235-245.
McMahon, J. E., McNeil, M., Turiel, I., and Benenson, P. (2005). *Analyzing and setting standards*. In S. Wiel & J. E. McMahon (Eds.), Energy-efficiency labels and standards: a guidebook for appliances, equipment, and lighting (2nd ed.). Washington, DC: Collaborative Labeling and Appliance Standards Program (CLASP).
McNeill, D. L., and Wilkie, W. L. (1979). *Public Policy and Consumer Information: Impact of the New Energy Labels*. Journal of Consumer Research, 6(1), 1-11.
Neter, J., and Wasserman, W. (1974). *Applied linear statistical models; regression, analysis of variance, and experimental designs*. Homewood, Ill.,: R. D. Irwin.
Norman, K. L. (1991). *The psychology of menu selection : designing cognitive control at the human/computer interface*. Norwood, N.J.: Ablex Pub. Corp.
Payne, J. W., Bettman, J. R., and Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge ; New York, NY, USA: Cambridge University Press.
Peterson, E. T. (2004). *Web Analytics Demystified: a Marketer's Guide to Understanding how Your Web Site Affects Your Business*: Celilo Group Media ; CafePress.
Quelle. (2006). *quelle.de auf einen Blick*. Retrieved 20 November, 2006, from http://karstadtquelle.de/download/Fact_Sheet_quelle.de_final.pdf
Reips, U.-D. (2002). *Standards for Internet-Based Experimenting*. Experimental Psychology, 49(4), 243-256.
Rubik, F., and Frankl, P. (2005). *The future of eco-labelling : making environmental product information systems effective*. Sheffield, UK: Greenleaf Pub.
Sammer, K., and Wüstenhagen, R. (2006). *The influence of eco-labelling on consumer behaviour - results of a discrete choice analysis for washing machines*. Business Strategy and the Environment, 15(3), 185.
Sanstad, A. H., and Howarth, R. B. (1994). *'Normal' markets, market imperfections and energy efficiency*. Energy Policy, 22(10), 811-818.
Schlomann, B., Gruber, E., Eichhammer, W., Kling, N., Diekmann, J., Ziesing, H.-J., et al. (2004). *Energieverbrauch der privaten Haushalte und des Sektors Gewerbe, Handel, Dienstleistungen (GHD).* Abschlussbericht des Fraunhofer-ISI Karlsruhe, DIW Berlin, GfK Nürnberg, Institut für Energetik und Umwelt Leipzig, und TU München an das Bundesministerium für Wirtschaft und Arbeit. Karlsruhe, Berlin, Nürnberg, Leipzig, München.
Shama, A. (1983). *Energy conservation in US buildings, solving the high potential/low adoption paradox from a behavioral perspective*. Energy Policy, 11(2), 148-167.
Sharda, R., Barr, S. H., and McDonnell, J. C. (1988). *Decision support system effectiveness: a review and an empirical test*. Management Science, 34(2), 139.
Shugan, S. M. (1980). *The Cost of Thinking*. Journal of Consumer Research, 7(2), 99-111.
Simon, H. A. (1955). *A Behavioral Model of Rational Choice.* The Quarterly Journal of Economics, 69(1), 99-118.

Stock, J. H., and Watson, M. W. (2003). *Introduction to econometrics*. Boston, MA: Addison Wesley.

Sutherland, R. J. (1991). *Market barriers to energy-efficiency investments*. Energy Journal, 12(3), 15.

Thorne, J., and Egan, C. (2002). *An evaluation of the Federal Trade Commission's EnergyGuide appliance label: final report and recommendations* (No. A021). Washington, DC: American Council for an Energy-Efficient Economy.

Tversky, A., and Kahneman, D. (1981). *The Framing of Decisions and the Psychology of Choice*. Science, 211(4481), 453-458.

US EPA. (1998). *Environmental Labeling Issues, Policies and Practices Worldwide* (No. EPA 742-R-98-009). Washington, DC: U.S. Environmental Protection Agency.

van Eimeren, B., Gerhard, H., and Frees, B. (2004). *ARD/ZDF-Online-Studie 2004. Internetverbreitung in Deutschland: Potenzial vorerst ausgeschöpft?* . Media Perspektiven(8/2004), 350-370.

VDEW. (2005). *Musterhaushalt 1998/2005. 40% Staatsanteil an der Stromrechnung*. Pressemeldung vom 21.11.2005. Berlin: Verband der Elektrizitätswirtschaft e.V.