

Life Cycle Cost Disclosure, Consumer Behavior, and Business Implications

Evidence From an Online Field Experiment

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Summary

Comprehensive assessments of final consumption have identified “housing” as a major contributor to total environmental impacts. Within this category, electrical-energy-using products are important. Do consumers opt for more energy-efficient household appliances if they are provided with life cycle cost (LCC)—that is, the sum of purchase price and operating cost estimated over the life span of the appliance? And what consequences does LCC disclosure have for business? Physical energy figures shown on appliance labels may be cognitively demanding for consumers, whereas monetary information promises to simplify the decision problem. Despite the rising interest in monetary cost disclosure, its effectiveness relative to physical cost disclosure has not been rigorously evaluated. This research approached the question of effectiveness with an online field experiment for washing machines. Customers of a commercially operating online shop were randomly assigned to two groups. The control group was provided with regular product price information; the treatment group received additional LCC information. A total of 2,065 clicks were recorded and analyzed with multiple regression that controlled for several product characteristics. The evidence suggests that LCC disclosure decreases the mean specific energy use of chosen washing machines by 0.8% ($p < 0.01$) and their mean specific water use by 0.7% ($p < 0.05$). As to business implications, LCC disclosure had no effect on the indicator of retail volume, which makes it unattractive for retailers to provide LCC on their own initiative.

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Introduction

A product that looks like a good deal at first glance may turn out to have high costs in the long run. Shoppers face this basic problem when trying to make decisions about energy-consuming durable household appliances. Can such a decision problem be simplified when physical energy information (e.g., kilowatt-hours) is converted into monetary values? And do consumers actually change their behavior when 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 to this question (McNeill and Wilkie 1979; Anderson and Claxton 1982), and has limited external validity. Moreover, previous research has had nothing to say about the business implications of providing life cycle cost information to consumers.

This article 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).

From an industrial ecology perspective, the approach described here responds to calls for implementation-oriented empirical research for sustainable consumption (Hertwich 2005) and, more specifically, for evaluations of the role of technology in influencing consumer behavior (Tukker et al. 2006). The focus on household appliances is based on life cycle considerations. In comprehensive assessments of final consumption, housing has been identified as one of the major contributors to total environmental impacts. Within the housing category, building structures, heating, and electrical-energy-using products are of key concern (Tukker and Jansen 2006).

Literature Review

For more than 20 years, analysts have been wondering why consumers do not invest in more energy-efficient technology at a faster pace. Those investments would be beneficial to consumers because they would reduce the item's 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* (Shama 1983; Jaffe and Stavins 1994; Sanstad and Howarth 1994).

Theoretical Background

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 those cost components is known as *life cycle costs* (Sanstad and Howarth 1994; McMahon et al. 2005). 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).

One factor that may account for the energy efficiency gap is missing information (Jaffe and Stavins 1994). Given humans' limitations in information processing (Simon 1955), the form of information may be important, too. When making intertemporal decisions about products on the basis of energy label information, consumers must expend cognitive effort, 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, such as the product's price, come in monetary units. Any such multicriteria comparison between products is cognitively demanding and may involve a trade-off between effort and accuracy in decision making (Payne et al. 1993). In view of consumers' inclination to reduce their cognitive effort, they may choose less-than-optimal products (Shugan 1980; Häubl and Trifts 2000) with respect to life cycle cost. Furthermore, the way consumers discount the future may have a large impact on their assessment of life cycle costs. Annual discount rates may vary considerably between individuals, even by an order of magnitude. Implicit consumer discount rates reported in the context of household appliances range up to about 300% per annum (Frederick et al. 2002; Deutsch 2007).¹ In sum, the energy efficiency gap may be partially caused by information problems.

In particular, the *form* of information may be important, influencing the complexity of the decision problem. One may simplify the problem by

presenting all *physical* figures that affect operating costs and come in different dimensions in a unified and consistent way: as *monetary* operating costs.

Monetary Operating Cost Disclosure

The first person to suggest providing monetary operating costs to consumers was Lund (1978). He saw life cycle cost disclosure as a potential “societal instrument” to affect consumers’ shopping decisions in the store. Likewise, the initial U.S. Energy Guide label for household appliances in 1979 carried an estimate of annual monetary operating cost as its centerpiece (U.S. EPA 1998). With the label’s revision in 1994, however, monetary units were no longer displayed prominently. 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 (FTC 2007). 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 other parts of the world, various energy information organizations host Web sites to provide consumers with monetary information and life cycle cost information for household appliances (Graulich 2006; Bush et al. 2007; Deutsch 2009).

Critics list three problems of monetary cost disclosure: first, spatial and temporal variability in energy prices; second, differences between individuals with respect to their implicit discount rates; and third, dissimilar individual usage behavior of appliances such as washing machines (Lund 1978). In view of this variability, so the argument goes, monetary cost disclosure on conventional static energy labels may be unfeasible, and only Web sites offer sufficient interactivity for adjusting cost parameters to individual needs.

Given those discussions and activities, the question is how effective monetary and life cycle cost disclosure actually are. The idea of simplifying physical information through monetary units has been supported by theoretical reasoning, and the practice has also been actively de-

manded by consumers (du Pont 1998; Thorne and Egan 2002). Similarly, ethnographic research on “folk units” of measurement has shown that U.S. consumers prefer monetary figures over physical figures when analyzing their energy use at home (Kempton and Montgomery 1982). Still, it is unclear to what extent those findings can be generalized to the entire population or to consumers in other countries.

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

Evaluations of Monetary Cost and Life Cycle Cost Disclosure

The focus of energy label evaluations has often been on studying awareness and understanding (Dyer and Maronick 1988; Rubik and Frankl 2005; FTC 2006), whereas only a few researchers have experimentally investigated labels’ effects on consumer behavior (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 were published in the early 1980s (McNeill and Wilkie 1979; Anderson and Claxton 1982; Hutton and Wilkie 1980). All of them focused on, as the dependent variable, the mean specific energy use of the products chosen by consumers. As independent variables, the studies varied the format in which energy information was provided to consumers (see the work by Deutsch [2009] for a more detailed comparison).

In two of the three studies, no significant difference ($p < 0.05$) could be found between the effect of physical energy information and monetary information on consumer behavior (McNeill and Wilkie 1979; Anderson and Claxton 1982). 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 limited in terms of external validity because they were not conducted in the field. They lacked tangible financial incentives that might have encouraged participants to concentrate on costs more strongly (Hertwig and Ortmann 2001). Moreover, the pool of participants was restricted to women. The third study was performed in the field, but the researchers encountered implementation problems (Anderson and Claxton 1982). Finally, the research technology available in the early 1980s—when the experiments described above were performed—did not allow researchers to observe consumer behavior in the way it can be tracked today by means of the Internet.² Overall, knowledge about the effect on consumer behavior of monetary energy cost disclosure in general, and life cycle cost disclosure in particular, is limited.

Experimental Online Shop

Hypotheses

I propose that life cycle cost disclosure will influence consumer behavior with respect to the choice of washing machines. My research hypotheses refer to the appliances' specific energy and water use, life cycle cost, the number of click-throughs, and product prices. The first hypothesis is about specific energy use.

Hypothesis 1: The disclosure of life cycle cost makes online shoppers opt for washing machines that are different in terms of their specific energy use.

Theoretically, simplifying energy information by expressing it in monetary units is likely to reduce consumers' cognitive effort and to affect their purchase decision. Analogously, a similar hypothesis, Hypothesis 2, refers to the potential change in specific water use of the chosen appliances.

Hypothesis 2: The disclosure of life cycle cost makes online shoppers opt for washing machines that are different in terms of their specific water use.

The two hypotheses are nondirectional—implying a more conservative two-tailed test—because of the ambiguity of prior research find-

ings. Although I do expect that the provision of life cycle cost will lead to lower specific energy and water use, I cannot a priori rule out the possibility that life cycle cost disclosure may instead increase such use. None of the experimental research closely related to life cycle cost disclosure mentioned above suggests that monetary information provision may in fact lead consumers to systematically buy *less* energy-efficient products. Yet the problem becomes more difficult when one broadens the perspective to the larger body of research on decision aids. In a small number of experiments from the early 1980s, users of decision support systems actually performed worse than the control group (Sharda et al. 1988). Such results are important because life cycle cost disclosure can be understood as a decision aid that helps the consumer to perform an otherwise computationally demanding task—that is, computing life cycle cost by hand for a list of product alternatives (cf. Häubl and Trifts 2000). In light of the research on decision support systems, life cycle cost disclosure may induce an increase or, conversely, a decrease in specific energy and water use.

Moreover, many consumers are already familiar with the energy label. In fact, prior exposure to the label information might have created in some consumers an intrinsic motivation to do something good for the environment. This motivation may be “crowded out” (Frey and Stutzer 2008) through an external intervention, such as life cycle cost disclosure. Consequently, the crowding-out phenomenon may counteract the effect of life cycle cost disclosure on energy and water use.

Finally, consumers' implicit discount rates may be comparatively high, due to, for example, a lack of liquidity (Sutherland 1991). If consumers value present costs much higher than future costs, the experimental treatment—which aims precisely at accounting for the future by disclosing future costs—may not make energy-efficient appliances more attractive. In summary, ambiguous experience with decision aids and the possibility of crowding-out and of high discount rates all question the proposed treatment effect.

I also examine whether the experimental treatment will change the estimated life cycle cost associated with the chosen appliances:

Hypothesis 3: The disclosure of life cycle cost makes online shoppers opt for washing machines that are different in terms of their estimated life cycle cost.

As to the economic impact of the Web site, the online shop is interested in any effect the treatment may have on turnover. Turnover equals price times quantity of washing machines sold. Therefore, both components of turnover have to be addressed. First comes price:

Hypothesis 4: The disclosure of life cycle cost changes the price of products put into the virtual shopping cart.

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

Hypothesis 5: The disclosure of life cycle cost changes the number of products put into the virtual shopping cart.

As before, the hypotheses are nondirectional. On the one hand, consumers may perceive life cycle cost disclosure as a helpful feature. As a consequence, the whole shopping experience may improve, and consumers may tend more strongly to put an item into the shopping cart.

On the other hand, they may dislike the fact that life cycle cost disclosure increases the overall information load and makes the Web site more cognitively demanding (Chiang et al. 2005). Therefore, it is an open question whether the treatment will bring about more or less turnover, relative to the control group.

Site Description

The experimental data were gathered from Quelle, a major German mail-order business that operates an online shop at www.quelle.de, with up to 9 million Web site 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's recommendation agent asks consumers about their preferences and ranks all washing machines according to these criteria. Consumers can drop or add machines, change their preferences, and compare all available wash-

ing 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.

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.

Display and Calculation of Life Cycle Cost

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

$$\text{Life Cycle Cost} = \text{Purchase Price} + \text{Operating Cost} \quad (1)$$

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 shows the experimental conditions in the Simple Search mode.

Life cycle costs (LCCs) were estimated as follows:

$$LCC = P + \sum_{t=1}^N \frac{C_t}{(1+r)^t} \quad (2)$$




where P = appliance purchase price (in euros), C_t = yearly operating cost (in euros per year), N = chosen time horizon (years), and r = discount rate.

For discontinuously working washing machines, operating costs were calculated as

$$C_t = (P_E \times C_E + P_W \times C_W) \times m \times k \quad (3)$$

where P_E = price of electricity (in euros per kilowatt-hour), C_E = specific consumption of energy (kilowatt-hours per cycle), P_W = price of water (in euros per cubic meter), C_W = specific

Table 1 Experimental conditions in the Simple Search recommendation mode

Experimental condition	Visual stimuli for sample washing machine
Control with regular price information	 <p>Miele W 4146 WPS Powerful and reliable</p> <p>At a glance Energy-saving washing machine (energy efficiency class A plus), at 1600 rpm an extremely high spin drying performance, washing performance class A, large capacity (6 kg) with automatic load detection</p> <p>1,159.95 €</p>
Treatment with additional operating cost and life-cycle cost estimates	 <p>Miele W 4146 WPS Powerful and reliable</p> <p>At a glance Energy-saving washing machine (energy efficiency class A plus), at 1600 rpm an extremely high spin drying performance, washing performance class A, large capacity (6 kg) with automatic load detection</p> <p>1,159.95 €</p> <p>Operating cost  (for a time horizon of 9,0 years)</p> <p>Life-cycle cost = Price + <u>estimated operating cost</u></p> <p>1,649.74 € = 1,159.95 € + 489.79 €</p>

Note: In the treatment group, operating cost could be adjusted by clicking on “estimated operating cost” and by changing the underlying default assumptions regarding time horizon, prices, and frequency of use. Original experimental stimuli were in German.

consumption of water (cubic meters per cycle), m = number of cycles per week (cycles per week), and $k = 52$ (weeks per 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 Web sites for consumers (Deutsch 2009).

Usage Assumptions and Their Adjustment

Users in the treatment group could choose to adjust the assumptions necessary for life cycle cost 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.

I could have implemented direct discounting 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). Because a pretest of the first option revealed that users did not comprehend this form of direct discounting, I substituted indirect discounting instead.

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

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	€/m ³	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 (Finck 2006)
Frequency of use	3	Cycles/week	2002	Rounded to integer (derived from 12.2 times per month; Schlomann et al. 2004)
Equivalent time horizon	9	Years	2006	Based on an implicit discount rate of about 6% and service life of 12.7 years; see Appendix for derivation

Note: €/kWh = euros per kilowatt hour; €/m³ = euros per cubic meter.

of an appliance vis-à-vis other appliances. In this fashion, direct discounting can be functionally replaced by an *equivalent time horizon* (see the Appendix for a derivation).

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

$$LCC = P + ETH \times (P_E \times C_E + P_W \times C_W) \times m \times k \quad (4)$$

where *ETH* = equivalent time horizon (in years).

When starting the recommendation agent, users saw 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.

Procedure

To keep the experimental conditions as realistic as possible, I gathered the data without obtaining participants' informed consent prior to participation.³ 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 questions, whereas in the Expert Search mode, users could specify up to 12 pref-

erences. Both modes covered questions regarding the general type of washing machine participants were looking for, 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 Internet cookies. Operating and life cycle cost for the treatment group were estimated on the basis of 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). Furthermore, both experimental groups could choose to see an in-depth comparison in matrix format with detailed product characteristics.

Data Collection and Preparation

During 2006,⁴ Mentasys collected clickstream data for washing machines from the server log files of the recommendation agent. Mentasys identified and removed hits from nonhuman user agents by means of blacklists for Internet Protocol addresses and user-agent information, and the company then delivered the resulting log files.

Estimation of operating cost

The estimation of operating cost relies on the assumptions shown below. You may individually adjust the default assumptions, which represent average values. This estimation does not reflect potential future changes in electricity or water prices.

<p>Frequency of use <input style="width: 50px; text-align: center;" type="text" value="3.0"/> times/week</p> <p>Water price <input style="width: 50px; text-align: center;" type="text" value="3.95"/> €/m³</p>	<p>Usage period <input style="width: 50px; text-align: center;" type="text" value="9.0"/> years</p> <p>Electricity price <input style="width: 50px; text-align: center;" type="text" value="0.16"/> €/kWh</p>
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Operating costs are estimated as follows:

Operating cost = (electr. price x electr. consumption + water price x water consump.) x frequency of use x usage period

e.g.: 526.89 € = (0.16 €/kWh x 1 kWh + 3.95 €/m³ x 0.045 m³) x 3 x 52/year x 10 years

This sample calculation serves illustrative purposes only, and it does not refer to any shown appliance in particular.

Figure 1 Display and adjustment of assumptions in the treatment group needed for the calculation of washing machines' operating cost. Original experimental stimuli were in German.

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 seemed to be an artifact of impatient clicking behavior. In such cases, I kept only the first click in the sample. Second, 9 users had a total of 20 or more click-throughs, which seemed suspiciously high to me. I considered these users to be nonhuman user-agents and dropped their observations. Overall, 2,065 click-throughs remained.

Measures

The dependent and independent variables used in this experiment refer to products that users put into the virtual shopping cart (click-throughs). The cart represents the online shop's central place from which consumers can directly proceed to checkout for billing and shipping.

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. Because life cycle cost by definition was not shown to users in the control group, these users had to be assigned life cycle cost estimates derived from common de-

fault assumptions about price and time horizon (see table 2). All dependent variables of interest are shown in table 3.

The independent variables included the machine's capacity (in liters) and dummy variable sets for energy efficiency class (A to F) and brand of a given appliance.

To cope with potential bias resulting from unidentified clicks by nonhuman user-agents, I checked how robust the results for energy use

Table 3 Dependent variables

<i>Dependent variable</i>	<i>Meaning/comment</i>
Energy	Specific energy use of appliance (kWh/standard cycle)
Water	Specific water use of appliance (m ³ /standard cycle)
Life cycle cost	Estimated life cycle cost of appliance (€), simulated for control group on the basis of default assumptions
Click-through count	Count of click-throughs per user
Price	Price of appliance (€)

Table 4 Descriptive statistics for overall specific energy use

All click-throughs	n	Mean energy	Median energy	SD energy	Min. energy	Max. energy
Control	1,040	0.975	1.02	0.118	0.57	1.36
Treatment	1,025	0.962	0.95	0.115	0.57	1.36
Total	2,065	0.969	0.95	0.116	0.57	1.36

Note: Energy is in kilowatt hours per cycle (kWh/cycle). n = number; SD = standard deviation; Min. = minimum; Max. = maximum.

were. Not only did I analyze all click-throughs, but I also scrutinized the smaller subset of each user's final click-through. Because I used each one's final click-through, no individual user could affect the estimates more strongly than any other user.

Models

I used the following regression model to test Hypothesis 1, that the energy-efficiency of chosen products is affected by the treatment:

$$\text{energy}_i = \beta_0 + \beta_1 \text{treatment}_i + \beta_2 Z_i + u_i \quad (5)$$

where *energy* = specific energy use (kilowatt-hours per 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:

$$\ln(\text{energy})_i = \beta_0 + \beta_1 \text{treatment}_i + \beta_2 Z_i + u_i \quad (6)$$

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.

To test Hypothesis 5, that the treatment affects the number of items put into the virtual shopping cart, I used a negative binomial regression model of the following form:

$$\text{ctcount}_i = \beta_0 + \beta_1 \text{treatment}_i + \beta_2 Z_i + u_i \quad (7)$$

where *ctcount* = number of click-throughs per user *i*.

Results

In sum, the online shop was visited by about 95,000 separately identifiable users, who were shown more than 160 different appliances from seven different brands. The prices of washing machines shown to consumers were negatively correlated with their operating costs when I used default assumptions (see table 2) and accounted for capacity. That is, more expensive appliances were, on average, associated with lower operating costs.

As explained in the *Procedure* section, users could choose between two recommendation modes, whose results are aggregated here. In what follows, I refer to the combined total of 2,065 items that users put into the virtual shopping cart.

Overall Energy Use, Water Use, and Life Cycle Costs

Both mean and median specific energy use were lower in the treatment group than in the control group (see table 4). The same was true for water use (see table 5). Mean life cycle cost were also lower in the treatment group, whereas median life cycle costs were the same as in the control group (see table 6).

Table 7 shows that when other factors are controlled for, the treatment affected both specific energy and water use. The treatment reduced energy use by 0.77% (Model 2) to 0.83% (Model 3). These results are significant at a 1% level.⁵ The treatment also reduced water use by 0.74% ($p < 0.05$), but it had no significant effect on estimated life cycle cost.

Overall Impact on Retail Volume

Turnover depends on prices and the number of click-throughs. The mean price was higher in

Table 5 Descriptive statistics for overall specific water use

All click-throughs	n	Mean water	Median water	SD water	Min. water	Max. water
Control	1,040	44.30	44	5.0	34	60
Treatment	1,025	43.81	42	4.9	34	60
Total	2,065	44.06	42	5.0	34	60

Note: Water is in liters per cycle (L/cycle). n = number; SD = standard deviation; Min. = minimum; Max. = maximum.

Table 6 Descriptive statistics for overall life cycle cost

All click-throughs	n	Mean life cycle cost	Median life cycle cost	SD life cycle cost	Min. life cycle cost	Max. life cycle cost
Control	1,040	953.3	901	134	798	1,650
Treatment	1,025	952.6	901	151	549	2,043
Total	2,065	953.0	901	143	549	2,043

Note: Life cycle cost is in euros. Life cycle costs were only shown to the treatment group and were therefore simulated for the control group on the basis of default assumptions. n = number; SD = standard deviation; Min. = minimum; Max. = maximum.

the treatment group (see table 8), whereas the mean number of click-throughs was higher in the control group (see table 9).

Tables 10 and 11 contain regression results for prices and the number of click-throughs, respectively. When other factors were controlled for,

the treatment did not have an effect on prices or click-throughs, at a 5% level of significance.

As a final point, I also investigated how sensitive the treatment effect was with respect to changes in perceived energy prices by adding the current price of regular gasoline in Germany as

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* (0.0053)	-0.0077** (0.0026)	-0.0083*** (0.0021)	-0.0083** (0.0026)	-0.0074* (0.0034)	0.00031 (0.0043)
ln(capacity)		0.86*** (0.0090)	0.95*** (0.0095)	0.96*** (0.014)	0.73*** (0.020)	0.48*** (0.026)
Mode			-0.0024 (0.0023)	-0.0041 (0.0028)	-0.034*** (0.0036)	0.034*** (0.0046)
Constant	-0.032*** (0.0038)	-1.49*** (0.016)	-1.49*** (0.0081)	-1.76*** (0.039)	2.92*** (0.023)	6.65*** (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 ²	0.003	0.762	0.840	0.846	0.537	0.459
n	2,065	2,065	2,065	1,437	2,065	2,065

Note: Robust standard errors are in parentheses. 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.

*p < 0.05, **p < 0.01, ***p < 0.001.

Table 8 Descriptive statistics for appliance prices

All click-throughs	n	Mean price	SD price	Min. price	Max. price
Control	1,040	488.5	132	299	1160
Treatment	1,025	488.6	129	299	1160
Total	2,065	488.6	131	299	1160

Note: Prices are in euros. n = number; SD = standard deviation; Min. = minimum; Max. = maximum.

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	47,665	0.022	0	0.22	0	15
Treatment	47,692	0.021	0	0.23	0	16
Total	95,357	0.022	0	0.22	0	16

Note: CT = click-through to put appliance into virtual shopping cart. n = number; SD = standard deviation; Min. = minimum; Max. = maximum.

a covariate. Alternative specifications included the price of gas in time-lagged form. Such modifications, however, did not change the experimental results noticeably, if at all. Therefore, those coefficient estimates are not reported explicitly here.⁶

Discussion

Experimental Outcomes

The negative estimates for the effect on specific energy use were significant at a 1% level. Substantively, however, they were much smaller (−0.83%) than what has been reported by

Table 10 Effect on appliance prices

	ln(price)		
	(1) Simple Search	(2) Expert Search	(3) Overall
Treatment	−0.0041 (0.0095)	−0.0093 (0.013)	0.00037 (0.0092)
ln(capacity)	0.11* (0.054)	−0.085 (0.068)	0.22*** (0.053)
Mode			0.074*** (0.0096)
Constant	6.40*** (0.12)	6.56*** (0.096)	6.88*** (0.057)
Efficiency class	Yes	Yes	Yes
Brands	Yes	Yes	Yes
Other features	Yes	Yes	Yes
Preferences	Yes	No	No
Adj. R ²	0.626	0.171	0.212
n	990	1,075	2,065

Note: Robust standard errors are in parentheses. Mode = recommendation mode (Simple Search, Expert Search). User preferences were logged only in the Simple Search mode.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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)
Inalpha constant	2.14*** (0.056)
Browsers	Yes
Pseudo R ²	0.237
N	95,357

Note: Standard errors of the negative binomial regression are in parentheses. Mode = recommendation mode (Simple Search, Expert Search).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hutton and Wilkie (1980), who found effects ranging from -12% to -27%. But when one takes into account differences in experimental settings, labeling systems, and energy prices, both findings still consistently suggest that life cycle cost disclosure guides consumers' choices toward products with higher energy efficiency. The same seems to be true with respect to specific water use, which was also reduced by the treatment.

The small size of the effect for energy and water may in part be explained by the crowding-out phenomenon (Frey and Stutzer 2008), according to which monetary incentives may crowd out consumers' environmental morale. If good energy label ratings were, prior to the experimental intervention, associated with environmental friendliness, life cycle cost disclosure might have diminished this intrinsic motivation in some consumers. Another factor that might have contributed to the small effect size is consumers' understanding of life cycle cost disclosure. By design, the experimental intervention was not described beforehand, and consumers were not made aware of the new feature through any education measure. Yet prior research has shown that supplementary education measures affect consumers' understanding and their use of additional information (Thøgersen 2005). Such measures might

therefore be necessary if one wanted to tap the full potential of life cycle cost disclosure.

Unlike specific energy and water use, estimated life cycle costs were not affected by the treatment. Because life cycle costs were—by definition—not disclosed to the control group, I had to simulate them to compare life cycle costs between the treatment and control groups.⁷ This simulation for the control group was based on common default assumptions (see table 2). Life cycle cost estimates for the treatment group, however, were derived from user-adjusted assumptions. Therefore, in the treatment group, the underlying assumptions deviated from the default assumptions. But even after I balanced this asymmetry and compared nonadjusted default assumptions for both experimental groups, none of the treatment coefficients was significant at a 5% level.

Given the online shop's business model, the number of click-throughs and the prices of clicked appliances jointly mattered for turnover. When other factors were controlled for, the treatment did not have an effect on prices or click-throughs at a 5% level of significance. Such a noneffect on turnover makes life cycle cost disclosure seem unattractive for retailers. Under these circumstances, the only positive effect on turnover can be expected in the form of a first-mover advantage. Those firms that are the first to implement life cycle cost disclosure voluntarily may gain customers from advertising the new feature correspondingly.

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 manually erase their cookies 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 Internet users 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 might 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 would tend to opt for relatively more energy-efficient appliances. As a consequence, the mean difference measured between the control and treatment groups would diminish—that is, such an 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 might have clicked on less efficient appliances after the change in experimental conditions. Such a scenario, however, seems 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 might have been somewhat confusing to them. In sum, the threats to internal validity described above might have led to a bias, which, in all likelihood, would have underestimated the treatment effect of life cycle cost disclosure on consumer behavior.

External Validity

First, the treatment effect might have varied with time. Interfering events, such as increases or decreases in energy prices, might have had an

impact on it. I tested this hypothesis by including the price of gasoline—a readily available indicator for energy prices—into my regression models. Given the nonsignificance of this variable, however, the treatment seems to have been relatively stable over time.

Second, it is impossible to say whether the users who visited 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 is 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.

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 nonhuman 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 used in this research were click-throughs that occurred when

consumers put items into the virtual shopping cart. Although these click-throughs refer to real consumer behavior, they cannot answer the ultimate question of whether a given consumer actually bought the product in the shopping cart. Because the online shop's software systems were not further integrated, however, I was not able to gather data on final purchases.

Conclusions

Disclosing estimated life cycle costs to shoppers made 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.⁸ Conversely, it seemed not to increase the online shop's retail volume, which makes it unattractive from a narrow 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). Moreover, the framing of costs and their coding as losses or gains may be important (Kahneman and Tversky 1979). That is, for life cycle costs, other formats may include a different framing of information as long-run *savings* (rather than *additional costs*) relative to a reference appliance (Alexandru et al. 2006; EC 2006a; Kaenzig and Wüstenhagen 2010). Finally, researchers could strengthen their study's internal validity by measuring actual final purchases and could increase external validity by performing similar research for different countries with other energy prices.

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Appendix

Adjustment of Assumptions

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. Because consumers may consider the investment in a washing machine as somewhat risky (Sutherland 1991; Frederick et al. 2002), the remaining difference between 4% and 6% was supposed to cover this risk premium.

On the basis of the default discount rate, the equivalent time horizon (ETH) was derived as follows. Fundamentally, operating costs calculated with an ETH must be the same as those computed through conventional discounting, which yields the general condition in equation (8):

$$\sum_{t=1}^T C_t (1+r)^{-t} \stackrel{!}{=} \sum_{t=1}^{ETH} C_t \quad (8)$$

where C_t = annual operating cost in year t , T = the known average service life of a given household appliance, r = discount rate, and ETH = equivalent time horizon. For constant C_t (as assumed here), the expression can be reduced to equation (9):

$$\sum_{t=1}^T (1+r)^{-t} \stackrel{!}{=} \sum_{t=1}^{ETH} = ETH \quad (9)$$

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. This was used as the default value throughout the experiment. Users could adjust the ETH according to their preferences, and when they did 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

$$LCC = P + ETH \times (P_E \times C_E + P_W \times C_W) \times m \times k \quad (10)$$

where P = appliance purchase price (in euros), P_E = price of electricity (in euros per kilowatt-hour), C_E = specific consumption of energy (kilowatt-hours per cycle), P_W = price of water (in euros per cubic meter), C_W = specific consumption of water (cubic meters per cycle), m = number of cycles per week (cycles per week), and $k = 52$ (weeks per year).

Notes

1. Kaenzig and Wüstenhagen (2010) present a conceptual model of the influence of life cycle cost information on consumer investment decisions that includes the type of life cycle cost information (explicit or implicit), the temporal framing of life cycle cost information (monthly, annual, or lifetime), the consumer-specific sensitivity to life cycle cost information, and information on the costs of alternatives (reference costs).
2. For a comprehensive review of studies on the effect of life cycle cost information on consumer investment decisions, see also the article in this issue by Kaenzig and Wüstenhagen (2010).
3. This procedure was approved by the institutional review board of the University of Maryland, College Park.
4. Due to proprietary information concerns, the exact period of time cannot be disclosed here.
5. In other words, there is a 1% possibility that these results were just due to chance.
6. Another variant of the experiment encompassed a different presentation of operating costs and life cycle costs. In that variant, long-run costs were presented in a more prominent way. Moreover, the default time horizon amounted to only about 5 years, which is equivalent to saying that the assumed implicit discount rate was higher. I could not detect a significant ($p < 0.05$) treatment effect on specific energy use in that variant, but 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 found in the work by Deutsch (2007).
7. Unfortunately, there is no way I can test whether consumers in the control group made life cycle cost assessments in the absence of life cycle cost disclosure. Yet I am interested in testing whether the explicitly disclosed life cycle costs of the treatment group differ from the costs that can be attributed to the choices made by consumers in the control group. This is why I had to simulate life cycle costs for consumers in the control group.
8. An exploration of the policy implications is beyond the scope of this article. See the work by Deutsch (2007) for a discussion of this question.

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