

ABSTRACT

Title of Document: THE EFFECT OF LIFE-CYCLE COST
DISCLOSURE ON CONSUMER BEHAVIOR

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For more than 20 years, analysts have reported on the so-called “energy paradox” or the “energy efficiency gap”, referring to the fact that economic agents could in principle lower their total cost at current prices by using more energy-efficient technology but, nevertheless, often decide not to do so.

Theory suggests that providing information in a simplified way could potentially reduce this “efficiency gap”. Such simplification may be achieved by providing the estimated monetary operating cost and life-cycle cost (LCC) of a given appliance—which has been a recurring theme within the energy policy and efficiency labeling community. Yet, little is known so far about the causal effects of LCC disclosure on consumer action because of the gap between the acquisition of efficiency information and consumer purchasing behavior in the real marketplace.

This dissertation bridges the gap by experimentally integrating LCC disclosure into two major German commercial websites—a price comparison engine for cooling appliances, and an online shop for washing machines. Internet users

arriving on these websites were randomly assigned to two experimental groups, and the groups were exposed to different visual stimuli. The control group received regular product price information, whereas the treatment group was, in addition, offered information about operating cost and total LCC. Click-stream data of consumers' shopping behavior was evaluated with multiple regression analysis by controlling for several product characteristics.

This dissertation finds that LCC disclosure reduces the mean energy use of chosen cooling appliances by 2.5% ($p < 0.01$), and the energy use of chosen washing machines by 0.8% ($p < 0.001$). For the latter, it also reduces the mean water use by 0.7% ($p < 0.05$). These effects suggest a potential role for public policy in promoting LCC disclosure. While I do not attempt to estimate the costs of such a policy, a simple quantification shows that the benefits amount to 100 to 200 thousand Euros per year for Germany, given current predictions regarding the price of tradable permits for CO₂, and not counting other potential benefits.

Future research should strive for increasing external validity, using better instruments, and evaluating the effectiveness of different information formats for LCC disclosure.

THE EFFECT OF LIFE-CYCLE COST DISCLOSURE ON
CONSUMER BEHAVIOR

By

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Chapter 1: Introduction

1.1 Statement of the problem

For more than 20 years, analysts have reported on the so-called “energy paradox” or the “energy efficiency gap”, referring to the fact that economic agents could in principle lower their total cost at current prices by using more energy-efficient technology but, nevertheless, often decide not to do so (Shama 1983; Jaffe and Stavins 1994; Sanstad and Howarth 1994; Howarth and Sanstad 1995).

Given the negative external effects due to energy-related carbon dioxide emissions (Watson 2001), the policy question is how to foster the effective and efficient diffusion of more energy-efficient technologies. On the demand side management part of the problem, policy interventions have included a combination of command-and-control and incentive-based mechanisms. The latter include product information requirements such as labeling. Labeling refers to the disclosure of information that otherwise would not be readily available to potential buyers (Stavins 2001, 31).

Energy efficiency labels for household appliances are used in the US, the European Union (EU) and other parts of the world (Wiel 2005, 21). In the EU, the overall energy efficiency of household appliances has increased since the mandatory introduction of labels in 1992, although it is hard to say to what extent this development is attributable to the labels (Enerdata sa and Fraunhofer ISI 2003, 62). Still, household appliances contribute substantially to overall energy consumption. They can be classified into six large appliances—refrigerators, freezers, washing machines, dish washers, TVs, dryers—

and various smaller ones. In the EU, the share of all large appliances in total energy consumption for electrical appliances and lighting amounted to 45% in 2001 (Enerdata sa and Fraunhofer ISI 2003, 52).

Since the early days of energy efficiency labeling, an important question has been whether information about energy use should be expressed in physical or monetary terms (McNeill and Wilkie 1979). Today, the debate is not settled; and policy-makers in the US and the European Union are currently considering changing their respective existing label formats to include monetary information (European Commission 2005a; Federal Trade Commission 2006).

Due to advances in communication technology, monetary information provision is also interesting in another respect. With the rise of the internet the way appliances are sold is changing, and online sales of large household appliances are growing. Varying by appliance type, their share in total German sales quantity ranged from 4% to 9% in 2004 (Gesellschaft für Konsumforschung 2005). For electronic commerce across all product categories, about 50% of all Germans report having incorporated available online information into their purchasing process, and about 45% of all Germans deem price comparisons to be the single most important element (Nielsen/Netratings 2004; van Eimeren, Gerhard et al. 2004).

Price comparisons on the internet exemplify a new kind of product information in the form of interactive decision aids (Guttman, Moukas et al. 1998). These aids are intended to reduce the cognitive effort of the consumer, and to increase the accuracy of her decision (Payne, Bettman et al. 1993; Häubl and Trifts 2000, 5). As to decision aids with respect to energy, energy information organizations in several countries offer online

energy tools (hereafter referred to as “energy efficiency calculators”). These enable consumers to convert the efficiency values of a given product into monetary operating cost. While differing in degree of interactivity, most of them additionally allow consumers to base this conversion on individual assumptions and preferences. The underlying logic is that consumers should be able to make a more conscious intertemporal trade-off between purchase price and future operating cost. A common way to reveal this trade-off is through the presentation of life-cycle cost (LCC)—that is, in its simplest form, the sum of purchase price and estimated operating cost for a given appliance (Hutton and Wilkie 1980; McMahon, McNeil et al. 2005, 160).

These two examples—conventional static labeling and energy efficiency calculators online—show that monetary cost disclosure is a salient energy policy problem. Yet, little is known so far about the causal effects of operating and life-cycle cost disclosure on consumer behavior because of the gap between the acquisition of efficiency information on the one hand, and the actual purchasing decision on the other hand (Wilbanks and Stern 2002).

1.2 Purpose of the dissertation

The purpose of this dissertation is to assess the effect of life-cycle cost disclosure on consumer behavior.

A survey of the literature suggests that the observed energy efficiency gap may be partially due to limited information and the cost of processing the information. Analysts from different theoretical backgrounds may differ in their exact characterization of the issue, but they agree that information provision and simplification can help reduce the

gap. Monetary cost figures, in turn, may simplify energy information by providing a common unit of measurement. In addition, consumers often demand monetary information when asked about their preferred information format (du Pont 1998; Thorne and Egan 2002). Yet, existing empirical findings about the effect of monetary information disclosure are ambiguous (McNeill and Wilkie 1979; Hutton and Wilkie 1980; Anderson and Claxton 1982).

In order to evaluate the effect of monetary information, I implemented two randomized online field experiments at distinct commercial websites in Germany that deal with household appliances. In both experiments, the control group was shown regular product information, whereas the treatment group received life-cycle cost estimates (i.e., the sum of purchase price and estimated operating cost) in addition to regular product information.

The first experiment for cooling appliances took place in a German “shopbot” (Smith and Brynjolfsson 2001). A shopbot differs from an online shop in that it only acts as an intermediary, and that it does not actually sell appliances itself. Consumer behavior was measured as click-throughs on products from the shopbot to final online retailers.

The second experiment focused on washing machines, and was conducted in a German online shop. As in the shopbot experiment, user reactions were evaluated by analyzing their click-throughs on appliances. Here, click-throughs represented washing machines that consumers had put into the virtual shopping cart.

1.3 Research questions

In order to better understand the potential effects of life-cycle cost disclosure both from an environmental policy and a business perspective, this dissertation asks:

- *Does life-cycle cost disclosure make online-shoppers opt for more energy-efficient household appliances?*
- *Does life-cycle cost disclosure make online-shoppers opt for more water-efficient washing machines?*
- *Does life-cycle cost disclosure have a positive or negative impact on retail volume?*

Answering these questions requires experimental life-cycle cost disclosure and an associated quantitative analysis. In addition, this dissertation answers the following questions through an evaluation of qualitative customer feedback:

- *How do online shoppers perceive life-cycle cost disclosure for household appliances?*
- *Do they easily understand the calculation of life-cycle cost?*
- *Do they feel that life-cycle cost disclosure helps them with the intertemporal trade-off between purchase price and future operating cost?*

1.4 Significance of the dissertation

The primary objective of this dissertation is to determine the potential benefits of policies that promote monetary life-cycle-cost disclosure. It differs from earlier studies in several respects:

First, the dissertation focuses on the effectiveness of monetary information provision. Past research in the area of environmental and energy labeling has

predominantly evaluated consumer perception. In going beyond awareness and understanding, this dissertation addresses the research need to measure how information provision is related to actual consumer behavior (Wilbanks and Stern 2002, 341-346). More specifically, to the best of my knowledge, it is the first experimental evaluation in the real marketplace where consumers could actively adjust the underlying assumptions of life-cycle cost estimation. Also, it simultaneously addresses the impact that life-cycle cost disclosure has on retail volume to evaluate the likely impediments to a potential wider implementation of energy efficiency calculators.

Second, the experiments in this dissertation were conducted as online field experiments. Methodologically, this approach has several advantages. Consumers in actual shopping situations had tangible incentives to find suitable products at low cost. Comparable laboratory experiments suffer from their hypothetical character and may not be generalizable to real purchasing situations. Ecological validity was high because effects attributable to being in an unfamiliar setting could be reduced (Reips 2002b, 247). Moreover, by relying on the internet, the experiments were purified from any experimenter effect and unreliable stimulus delivery due to human failure.

In sum, by evaluating the effectiveness of life-cycle cost disclosure in a realistic setting, this dissertation makes a substantial contribution to better understanding the potential gains from life-cycle cost disclosure for environmental policy.

1.5 Organization of the dissertation

The remainder of this dissertation is organized as follows. Chapter 2 presents a survey of the relevant literature. It introduces the energy efficiency gap (2.2) and provides

theoretical approaches that have been used to explain this gap (2.3). One relevant factor in explaining the gap is missing information, or too complex information. Potential solutions include information provision in the form of energy labeling and monetary cost disclosure (2.4). The latter is especially attractive from a cognitive perspective because it reduces the number of dimensions in a complex decision problem by converting physical energy units into monetary units. This simplification has been a recurring theme within the energy policy community, and has gained renewed attention with the rise of the internet. In several countries, energy information organizations nowadays provide operating cost estimates for household appliances on specific websites. Still, few evaluations have assessed whether monetary information effectively adds anything to physical energy use information with respect to consumer behavior. The small number of experimental studies available contains ambiguous results (2.5). Therefore, it may be instrumental to make use of the internet as a research tool (2.6). In light of the prior findings, I discuss the possibility of using online field experiments for assessing the causal effect of life-cycle cost disclosure on consumer behavior (2.7).

Chapter 3 describes the shopbot experiment. The data from a major German web portal consist of observations for refrigerators, fridge-freezers and freezers (3.2). All variables of interest refer to appliances for which users have clicked-through from the shopbot to final online retailers. The research hypotheses (3.3) concerning the effects of life-cycle cost disclosure on energy use, the estimated life-cycle cost of clicked appliances, and the number of click-throughs are tested. In terms of methods, these hypotheses are tested in two-group posttest-only randomized experiments with multiple regression analysis (3.4). Two distinct experimental treatment rounds are conducted. I

find that in the first treatment round, life-cycle cost disclosure reduces the overall mean energy use of clicked cooling appliances by 2.5%; and it leads to a decrease in click-throughs from the shopbot to final retailers by about 23%. Conversely, estimated life-cycle cost does not differ significantly between experimental groups (3.5). The most important limitations to the experimental results have to do with the reliance on browser cookies and potential self-selection bias (3.6).

Chapter 4 reports results from the online shop experiment. The data contains observations from an experimental recommendation agent for washing machines (4.2). In addition to energy use, estimated life-cycle cost, and click-throughs, the research hypotheses also refer to water use (4.3). As in the shopbot case, the hypotheses are tested in two randomized experiments and with the aid of multivariate methods. Furthermore, I conduct in-depth interviews with selected customers from the treatment group (4.4). I find that life-cycle cost disclosure for washing machines is associated with a reduction in overall mean energy use by about 0.8%, and with a reduction in water use by about 0.7%. Supplementary results from the customer interviews indicate that the visual presentation of life-cycle cost may be decisive for the outcome (4.5). All results are discussed in section 4.6.

In chapter 5, I summarize all experimental findings (5.1) and draw policy-relevant conclusions (5.2). Although the evidence suggests that life-cycle cost disclosure reduces energy use, policy-makers should weigh the costs and benefits of a potential implementation. While the costs of implementation cannot be quantified, I provide an order-of-magnitude estimate of the benefits for Germany. These amount to 100 to 200 thousand Euros per year, given current predictions regarding the price of tradable permits

for CO₂. Finally, future research should strive for increasing external validity, using better instruments, and evaluating the effectiveness of different information formats for life-cycle cost disclosure (5.3).

Chapter 2: Review of the literature

2.1 Introduction

The following literature review introduces the discussion on the energy efficiency gap (2.2), presents theoretical approaches to the gap (2.3), compares conventional labeling with monetary cost disclosure (2.4), describes the evidence regarding the effectiveness of labeling (2.5), provides an overview of internet-based research approaches (2.6), and discusses the possibility of using online field experiments for assessing the effect of life-cycle cost disclosure on consumer behavior (2.7).

2.2 The energy efficiency gap

The fact that economic agents could in principle lower their cost at current prices by using more energy-efficient technology but, nevertheless, often decide not to do so has been called the “energy paradox” or “energy efficiency gap” (Shama 1983; Jaffe and Stavins 1994; Sanstad and Howarth 1994; Howarth and Sanstad 1995).

At the core of the energy policy debate about the efficiency gap are the issue of market barriers versus market failures, and a possible justification of governmental intervention. Market *barriers* are referred to in explanations of why investment options shown to be cost-effective at current prices have only limited success in the market (Jaffe and Stavins 1994, 804). By contrast, a market *failure* points to a situation that leads to inefficient resource allocation. Different from the former, the latter may justify government intervention in the market, if such an intervention would in fact increase market efficiency (Sutherland 1991).

Evidence of the energy efficiency gap has been interpreted in several ways. On the one hand, implicit discount rates estimated in the context of energy-related consumer decisions are much higher than the rate of return on available alternative investments (see 2.4.4.2 below). That is, the estimates seem to run counter to the efficient market hypothesis (Howarth and Sanstad 1995). In view of those findings, Sanstad and Howarth (1994) discuss several market imperfections related to energy efficiency, such as the existing regulatory environment, imperfect information, asymmetric information, transaction costs, imperfections in capital markets, and bounded rationality (see 2.3.2 below) in energy decisions. In their view, many such market imperfections can be interpreted as market failures (Sanstad and Howarth 1994).

Opponents, on the other hand, judge the evidence of the efficiency gap differently. Sutherland (1991) discusses possible alternative explanations. Whereas professionals make repetitive decisions with respect to energy efficiency investments and can therefore distribute search cost over several investments, private households must amortize their search and information costs with one or very few purchases. Given that investments with respect to energy efficiency are risky and illiquid for consumers, it is rational for consumers to demand a rate of return that is above the average market rate for risk-free and liquid assets. The author concludes that several market barriers, such as misplaced incentives, high initial cost, illiquidity, and high risk concerning energy efficiency investments, do not represent market failures (Sutherland 1991). Along the same line, Hassett and Metcalf (1993) reject notions of market failure or consumer irrationality with respect to the energy efficiency gap. Instead, they identify sunk cost and uncertainty regarding future conservation savings as a rational explanation for

consumers' implicit discount rates. According to their simulations, consumers' "hurdle rates" should be about four times greater than the standard rate (Hassett and Metcalf 1993).

Overall, analysts do not agree on the extent to which the observed energy efficiency gap represents market failure. Nevertheless, many agree that limited information does matter, and that—depending on its characteristics—it may even represent market failure (Sutherland 1991; Jaffe and Stavins 1994; Sanstad and Howarth 1994).

2.3 Theoretical approaches to the energy efficiency gap

The human behavior that leads to the observed energy efficiency gap can be seen through two lenses; a rational choice lens (2.3.1), or, alternatively, a broader behavioral lens (2.3.2). Although such a dichotomization does not do justice to the more differentiated existing research landscape, it is instrumental for the purpose of this dissertation. A broader exposition of behavioral decision research can be found in Jungermann, Pfister, and Fischer (2005) in general, and in Camerer and Loewenstein (2004) on behavioral economics in particular.

2.3.1 Rational choice perspective

From a rational choice perspective, consumers are expected to obtain energy-related services at least cost because cost minimization is necessary for utility maximization. When costs accrue at different points in time—as in the case of operating cost of durable goods—cost minimization conceptually involves intertemporal allocation. At a practical level, the typical approach to calculating least cost is the life-cycle cost approach

(Sanstad and Howarth 1994, 812; McMahon, McNeil et al. 2005, 158). Life-cycle costing can be understood as an application of investment theory to consumer behavior (Stern 1978). Also, it includes explicit or implicit discounting on the part of the consumer (Liebermann and Ungar 2002, 730). For the purpose of discounting, economists traditionally rely on the discounted utility model, which condenses all motives that may underlie the decision into one single variable—the discount rate (Frederick, Loewenstein et al. 2002).

Within a standard economic framework, the observed behavior that leads to the energy efficiency gap can be explained by market failures, such as the underprovision of information about the relevant technology, uncompensated positive externalities from technology adoption, and principal-agent problems caused by a separation of the user and the buyer of a given technology. Alternative explanations unrelated to market failure interpret the observed behavior of energy users as actually optimal. The explanations include uncertainty about future energy prices and associated, relatively high discount rates, undesirable product characteristics of more efficient technology, private transaction costs of information acquisition and adoption, and heterogeneity in the population of potential technology adopters (Jaffe and Stavins 1994, 805).

2.3.2 Broader behavioral perspective

Representatives of a broader behavioral perspective acknowledge the limits to intendedly rational behavior and rather work within a framework of “bounded rationality” (Simon 1957, 198). Moreover, they may not approach human actions as being driven by a single type of optimizing behavior. Instead, they may stress the existence of different heuristics

for problem solving—simple rules for searching, stopping and decision-making (Simon 1955; Payne, Bettman et al. 1993; Gigerenzer and Selten 2001).

A related stream of research in economics is transaction cost theory (Coase 1937; Williamson 1975) with its emphasis on environmental and human factors that may affect market exchanges. In the underlying information-processing paradigm (Miller 1956), it is not only the availability of information that matters, but also the way in which humans, with their limited cognitive capacities, are able to handle it; for example, energy efficiency information on product labels.

When incorporating label information into their purchasing decisions, humans try to reduce their cognitive effort (Shugan 1980). The chosen option can be described as a trade-off between effort and accuracy (Payne, Bettman et al. 1993) and may frequently be suboptimal relative to a benchmark situation without any decision cost. That is especially true for complex decision processes in which alternative options are difficult to compare (Häubl and Trifts 2000, 5). As to labels for household appliances, they provide information in distinct dimensions, such as *kilowatt-hours* (for electricity) or *liters* (for water) that may be difficult to compare to a product's price in *dollars* or *euros*. The more cognitively oriented view of consumer behavior suggests that consumers may choose products that are less than optimal with respect to their operating cost.

Representatives of both rational choice and broader behavioral approaches agree, at a general level, that human decision-making is influenced by prices and information. According to the broader behavioral perspective, individuals' decisions do not, however, depend solely on prices, but are also influenced by a possible commitment to save energy, as well as by personal values and beliefs (Stern 1986). The relative importance of

the different motives that drive human behavior may vary with specific circumstances and situations (Stern 1992).

Moreover, the framing of outcomes may be important. According to prospect theory, individuals will mentally represent alternative outcomes as losses or gains relative to a reference point. It is not the final state that matters, but the relative change. In addition, an individual is loss-averse, so that losing or gaining the same amount of money are not considered as symmetrical events. Both the way the reference point is perceived and the way the outcomes are framed can be affected by their presentation and by an individual's prior expectations (Kahneman and Tversky 1979). In the context of energy cost disclosure, that becomes relevant when thinking about consumers' frames of reference. Additional costs may be coded as losses and savings may be coded as gains (Tversky and Kahneman 1981).

Finally, the standard economic discounted utility model has been scrutinized by behavioral researchers. Analyses conducted over the recent decades have cast doubt on the assumption that the discounted utility model can appropriately describe actual human behavior. The issue of discounting will be considered in more detail in section 2.4.4.

In summary, the observed energy efficiency gap may be partially explained by limited information and the cost of processing the information. Analysts from different backgrounds may differ in their exact characterization of the issue, but they generally seem to suggest that information provision and simplification can help reduce the problem. Monetary cost figures, in turn, may simplify energy information by using a common unit of measurement.

2.4 Energy efficiency labeling and monetary cost disclosure

This section covers energy efficiency labeling (2.4.1), consumers' demands for monetary information (2.4.2), operating and life-cycle cost disclosure (2.4.3), a discussion about the inclusion of operating costs in energy labels (2.4.5), and the application of operating cost disclosure on the internet (2.4.6).

2.4.1 Energy efficiency labeling

Energy efficiency labels can be either *endorsement labels* or *comparative labels*. An endorsement label, such as, for example, the US Energy Star, shows the approval of a certain authority, stated in terms of pre-specified criteria; whereas comparative labels allow consumers to compare different products in terms of their energy efficiency (du Pont, Schwengels et al. 2005, 91). Given the inherently comparative nature of life-cycle cost disclosure, this dissertation focuses solely on the latter. More general reviews of labeling can be found elsewhere (Gallastegui 2002; Banerjee and Solomon 2003; Leire and Thidell 2005).

Using a categorical or continuous scale, comparative labels rank a product's performance within a spectrum of alternative products. Alternatively, such labels provide information only about the product under consideration, leaving to the consumer the responsibility to compare the information with that from other products. Whereas labels with a continuous scale usually provide additional information about energy use, cost, and further product characteristics (e.g., quality of lighting or amount of noise), labels with a categorical scale may or may not contain such information. Although the international trend is toward the adoption of categorical labels, the US and Canada still

use continuous energy labels (du Pont, Schwengels et al. 2005, 89-94).

A periodical redefinition of categorical labels becomes necessary for the following reason. Once label categories have been set, the affected products tend to become increasingly efficient. Eventually, all of them might fall into the most energy-efficient category. At that point, the categories no longer serve their intended purpose; so, they need to be redefined or otherwise adjusted. Such adjustments may entail the revision of current categories or, alternatively, the introduction of new categories that represent higher efficiency (du Pont, Schwengels et al. 2005, 108).

2.4.2 Consumer understanding of, and demand for monetary information

Monetary information might help consumers better understand energy information. An early ethnographic study described “folk units” of measurement; that is, consumers’ quantifications of their energy use at home. The study sample consisted of 30 Michigan families who were interviewed without predefined questions. In the context of utility energy bills, the researchers showed that consumers better related to dollars spent per month rather than to physical units. The same held true for comparisons of different fuels and the interpretation of national energy policy. None of the interviewees mentioned abstract energy units, such as *joules* or *British thermal units*, and few referred to commercial units, such as *kilowatt-hours*. The researchers concluded that folk measurement in dollars was useful from a consumer’s perspective because it allowed to directly compare different household expenditures with energy cost (Kempton and Montgomery 1982).

This preference for monetary information has also been shown in another context.

Thorne and Egan (2002) conducted research with consumer focus groups regarding a new design of the Energy Guide label. Asked about an ideal label, participants suggested, among other things, including and highlighting estimated annual operating costs. Overall, Thorne and Egan stressed the consumers' strong preference for monetary units over physical units of energy efficiency (Thorne and Egan 2002). The same was observed by du Pont (1998, 8-15), whose interview respondents "overwhelmingly" favored dollar amounts over kilowatt-hours.

Even though such insights gained from qualitative studies suggest consumer understanding of monetary information, the extent to which they might represent a larger population of shoppers is unknown (Kempton and Montgomery 1982; Thorne and Egan 2002). Nor can the findings predict what kind of average consumer behavior we should expect as a result of life-cycle cost provision—which calls for a quantitative evaluation.

2.4.3 Operating cost and life-cycle cost disclosure

The notion of life-cycle cost (LCC) disclosure for consumers—as opposed to firms—goes back more than 30 years, when the Center for Policy Alternatives at MIT conducted several LCC studies, partly as guidance for the US Energy Policy and Conservation Act of 1975. Lund (1978) described the early aspirations, the largest problem, and a possible solution related to LCC disclosure.

LCC is given as the sum of purchase cost, annual operating and maintenance costs, and disposal cost, discounted over the lifetime of an appliance (Lund 1978). Variations of that definition may leave out the costs for disposal, installation, or maintenance. For comparing alternatives, that may not matter, if those costs are

uncorrelated with energy efficiency (McMahon, McNeil et al. 2005).

Fundamentally, Lund saw LCC disclosure as a potential “societal instrument” (Lund 1978, 17) for influencing consumers’ buying decisions. The largest challenge to LCC disclosure is the variation among consumers’ preferences and situations, such as usage rate, discount rate, regional climate, etc. Simply calculating a reference LCC based on national averages does not provide for deviations and renders cost figures “virtually meaningless” for the individual consumer (Lund 1978, 19). Lund’s vision for countering the challenge was a computer-based decision-support system that would be readily available to consumers for calculating—at home or at the point of purchase—their individualized expected LCC. In Lund’s words, such a system “would revolutionize” the way consumers make decisions (Lund 1978, 21). With the rise of the internet and of mobile communication technologies, that vision has become feasible.

2.4.4 The role of time preference in life-cycle cost analysis

Time plays an important role in life-cycle cost analysis. In any practical application, one must consider discounting (2.4.4.1), empirically estimated implicit discount rates (2.4.4.2), and ways to elicit discount rates from consumers (2.4.4.3).

2.4.4.1 Discounting in life-cycle cost analysis

The life-cycle cost of a given appliance is the sum of purchase cost and other associated costs, discounted over the lifetime of the appliance. For discounting, economists traditionally rely on the discounted utility model, as introduced by Paul Samuelson when attempting to model decisions regarding intertemporal choice. The discounted utility model condenses all motives that may underlie the decision into one single variable—the

discount rate. Research conducted over the recent decades has, however, cast doubt on the assumption that the discounted utility model can appropriately describe actual human behavior.

A wide array of empirical studies, including both field and laboratory studies, shows huge variation in discount rates—not only between studies, but also for given individuals. Those variations in annual discount rates, ranging from minus six to infinity, suggest that individuals consider many aspects of a given decision when making intertemporal choices, and that those aspects may differ with varying circumstances. Even more, variations in discount rates for a given individual hint at multiple motives, with different implications for attitudes about the future that may be at work in the same person.

The discount rates reported in the literature are derived from observations that are supposed to satisfy a net present value equation. The rates can be inferred from actual consumer decision making in the field, or by asking consumers to evaluate intertemporal trade-offs that may be either real or hypothetical. Potential confounding factors include consumption reallocation, intertemporal arbitrage, concave utility, uncertainty, inflation, expectations of changing utility, as well as habit formation, anticipatory utility, and visceral influences.

Frederick et al. (2002) suggest applying discounting models that have proven most appropriate for a given domain. With respect to domains of multi-motive discounting models, they discriminate drug addiction, extended experiences, and brief, vivid experiences. For example, models of drug addiction may incorporate habit formation, visceral factors, and hyperbolic discounting (Frederick, Loewenstein et al.

2002, 351-394).

Liebermann and Ungar describe life-cycle cost analysis as an investment choice. They illustrate the intertemporal trade-off with two products, A and B, that have the same features except for their purchase prices (P_A ; P_B) and operating costs (C_A ; C_B). Product A has the lower purchase price ($P_A < P_B$) and the higher operating cost ($C_A > C_B$), whereas product B has a higher purchase price and lower operating cost.

$$P_B - P_A = \sum_{t=1}^N \frac{C_A - C_B}{(1+r)^t}$$

Choosing product B can be interpreted as investing the amount ($P_B - P_A$) in order to receive the return ($C_A - C_B$) per period. The formula calculates the “rate of return”—the implicit discount rate—at which consumers are indifferent between product A and B (Liebermann and Ungar 1983, 380).

2.4.4.2 Estimated implicit discount rates with respect to appliances

Implicit consumer discount rates that have been reported in the context of household appliances range from about 0% to 300%. See the table below for the estimates from three studies.

Table 1: Empirically estimated implied discount rates

<i>Reference</i>	<i>Appliance</i>	<i>Real discount rate</i>	<i>Comment</i>
(Hausman 1979)	Air conditioners	5% to 89% (mean: 25%)	Dependent on income class; US study
(Gately 1980)	Refrigerators	45% to 300%	Depending on assumptions about electricity cost; US study
(Meier and Whittier 1983)	Refrigerators	$r < 35\%$ (40% of consumers) $35\% < r < 60$ (~20% of consumers) $r > 60\%$ (~40% of consumers)	Combined data from different US regions (Pacific, South, Midwest, East); assumption that there are no discount rates less than 20% or above 120%

In a more recent study, a representative sample of German adults was given the hypothetical choice between two refrigerators that were equal in all respects except purchase price and energy efficiency. The more expensive product was the more energy-efficient, and it was preferred by 82% of the respondents; 12% favored the other product and 6% could not decide (“I do not know”) what product to choose (Kuckartz and Rheingans-Heintze 2004, 81). See the table below for the implicit discount rates that can be inferred from the finding.

Table 2: Implied discount rate with respect to appliances for German consumers

<i>Reference</i>	<i>Appliance</i>	<i>Discount rate</i>	<i>Comment</i>
(Kuckartz and Rheingans-Heintze 2004)	Refrigerator	$r < 18\%$ (82 % of consumers) $r > 18\%$ (12 % of consumers) $r = 18\%$ (6 % of consumers)	German study; inferred discount rate is based on my own calculation that assumes an average refrigerator lifetime for Germany of $N=14.4$ years (GfK 2006) <i>Model A</i> (12% of survey respondents): $P_A = €329, C_A=€35/\text{year}$ <i>Model B</i> (82% of survey respondents): $P_B = €379, C_B=€25/\text{year}$ $P_B - P_A = \sum_{t=1}^N \frac{C_A - C_B}{(1+r)^t} \Rightarrow r \approx 18\%$ (see 2.4.4.1 for the formula)

2.4.4.3 Experimental elicitation of discount rates

In experimental studies, discount rates are commonly elicited by means of matching tasks, pricing tasks, rating tasks, or choice tasks—the last being the most common. All of them can be conducted hypothetically; that is, by referring to hypothetical situations without real rewards. At a general level, no clear difference in discount rates could be observed between research involving hypothetical rewards, as opposed to that involving real rewards.

Choice tasks require subjects to choose between two rewards—one that is immediate; the other, delayed. A subject may be asked, for example, whether he prefers 100 units of something today over 110 units a year from today. In order to go beyond determining merely upper and lower bounds for discount rates, subjects may be presented a series of choice tasks with variations in rewards or delays. The variations allow the

researcher to determine the discount rate more precisely. Conducting research via a series of choice tasks may suffer from the „anchoring effect”, which means that the subject’s first choice may influence subsequent choices.

Matching tasks requires subjects to fill in the blank in a given equation, such as „\$100 now = ____ in one year“. The process makes it easier to determine exact discount rates through the point of indifference, and it does not suffer from the anchoring effect. Depending on what part of the equation is left blank, however, results obtained through this procedure may differ considerably.

Rating tasks requires subjects to rate the attractiveness or unattractiveness of an outcome that occurs at a particular time.

Pricing tasks requires subjects to give a willingness to pay to obtain or avoid an outcome that occurs at a particular time (Frederick, Loewenstein et al. 2002, 386-388).

2.4.5 Operating cost disclosure on labels

Following the early work at MIT, the inclusion of operating and life-cycle costs has been considered in the context of labeling. In 1979, the US Federal Trade Commission (FTC) presented its original Energy Guide label design for appliances that—except for room air conditioners and furnaces—showed estimated annual operating cost as the dominant piece of information, and a relative ranking of the product with respect to other available models. According to the then-current FTC regulations, a 15% change in energy prices with respect to the baseline for the label entailed a renewed calculation of operating cost for new labels. As a consequence, identical appliance models showing different operating costs may have been available at the same retailer at a given point in time (US EPA

1998). In addition, critics pointed out that local and temporal variance in energy prices risked confusing those consumers whose rates were far from the national average. Those problems led to a revision of the Energy Guide label in 1994. In its current design, it uses physical units as primary information—supplemented with annual operating cost in small font at the bottom of the label (Banerjee and Solomon 2003; du Pont, Schwengels et al. 2005). Still, the debate is not settled. Some critics have, again, demanded monetary information to make the label easier for consumers to understand. To clarify such and other hypotheses, the FTC has recently proposed consumer research on the perception and comprehension of the Energy Guide label to test alternative label designs (Federal Trade Commission 2006).

Along the same lines, operating cost disclosure is currently being considered in the European Union in general, and in Germany in particular. The European Commission recently presented its Green Paper on energy efficiency, which considers “improved product labeling” as a potential measure for reducing the energy efficiency gap (European Commission 2005a). Subsequent feedback from interested parties indicates that many would like to have energy labels show savings, cost and life-cycle cost for appliances and other products, such as cars (European Commission 2006b). In Germany, energy labeling is being discussed as part of the United Nations Marrakech process on sustainable consumption and production. Manufacturer and retail representatives are considering providing operating cost on household appliances—on a voluntary, but standardized basis, and as a supplement to the conventional European energy label (Bundesministerium für Umwelt 2006).

2.4.6 Consumer websites with operating cost information

Finally, operating cost and LCC disclosure are at the core of many existing consumer websites operated by energy information organizations in Europe and elsewhere abroad. Given their interactive character, they are in line with Lund's (1978) notion of computer-based LCC decision aids for consumers. They provide varying ranges of appliances to consumers who are about to buy a new appliance. Their incrementalist approach is different from more comprehensive, whole-building energy audit tools such as the US Home Energy Saver. See Mills (2004) for a recent review of tools for residential energy analysis.

Table 3 evaluates websites from energy information organizations in Europe and Australia. The websites' main purpose is to provide simple, static cost estimates over the lifetime of a given appliance that assume constant prices, and that are based on the physical efficiency performance of the appliances. The list is not intended to be comprehensive. Rather, it covers those websites mentioned in the recent literature. It does not include product ratings regularly published by organizations, such as Consumer Reports in the US or "Stiftung Warentest" in Germany, although they may offer similar information.

Table 3: Websites that provide lifetime operating costs for household appliances

<i>Program</i>	<i>Country</i>	<i>Reported self-evaluation</i>	<i>Reference</i>
EcoTopTen ^c	Germany	Rising number of hits and visitors	(Graulich 2006)
Energiesparende Geräte ^{d, e, f, g}	Germany	n/a	(Siderius 2003)
Energyrating ^{e, f, g, h}	Australia	Over one million user hits in 2004	(Harrington, Foster et al. 2005; Australian Greenhouse Office 2006)
European Appliance Information System ^d	Europe	No. of hits varies from a few hundred to several thousands/month	(European Commission 2005b; Alexandru, Caponio et al. 2006; European Commission 2006a)
Initiative Energieeffizienz – Gerätedatenbank ^{a, e, g}	Germany	n/a	(Agricola and Ahrens 2005; DENA 2006)
Spargeräte ^{e, f, g, h, i}	Germany	n/a	(Graulich 2006; Niedrig-Energie-Institut 2006)
topten.ch ^{b, h}	Switzerland	One million visitors and 27 millions hits in 2005	(S.A.F.E. 2005; Bush, Attali et al. 2006)

Note: This list of websites is illustrative, not comprehensive; n/a – not available; additionally offered information and interactive elements:

- a) price range of product
- b) price of product
- c) annualized life-cycle cost (i.e. annualized sum of purchase price and operating cost)
- d) savings compared with a reference appliance
- e) adjustable tariffs
- f) adjustable lifetime
- g) adjustable frequency of use, for example, for washing machines
- h) sortability of products
- i) directly links to retailer for selected products

The websites are evaluated on several criteria. Most of them do not provide information about purchase price, which means that consumers cannot easily calculate LCC by themselves. Those that do offer price information provide either one single price (e.g., the suggested retail price) or a price range for each product. Nearly none of them, however, is connected to online retailers; so, consumer cannot easily access purchase price information for each product. An exception is the German “Spargeräte” website, which provides links to a specific retailer for selected products. Two of the websites also provide the *savings* that result from comparing the operating cost of one appliance with

that of a reference appliance.

Websites vary in their degree of interactivity. On the most static website, consumers cannot adjust any of the default assumptions that underlie the calculations. On the most interactive website, users can adjust lifetime, electricity tariffs, frequency of use, and sorting of the displayed products. None of the websites explicitly mentions discounting, and nowhere can discount rates be specified by consumers. That appears to be problematic because of the variation in individuals' discount rates that have been reported in the literature. In the context of household appliances, implicit discount rates have been shown to range from about 0% to 300% (see 2.4.4.2).

Finally, four of the seven websites mention a form of self-evaluation. They measure their success by the number of online hits and visitors, which is derived from server log files. None of them indicates whether they have attempted to evaluate their effect on consumer behavior in a more substantial sense, as described in the following section.

In summary, many people in the energy efficiency community seem to believe in the power of operating cost and LCC disclosure. That view seems to be supported by ethnographic studies and exploratory research, with small numbers of interviewees, in which consumers have demanded monetary information. Still, the policy-relevant question is whether LCC disclosure actually affects consumer behavior.

2.5 Evaluating the effectiveness of labels and operating cost disclosure

Methodologically, label evaluations may rely on observational or experimental data, and the analysis may focus on micro-level consumer comprehension, perception, awareness

or behavior, or, alternatively, on the macro-level market effects of labeling. This section introduces research on awareness and market transformation (2.5.1), experimental research on antecedent strategies in general (2.5.2), and experimental research on labels with monetary information in particular (2.5.3).

2.5.1 Research on awareness and market transformation

Although, from a policy perspective, the decisive dependent variable at the micro-level is consumer behavior, past research has predominantly investigated consumers' label awareness and understanding. A theoretical justification is that behavior is assumed to be predictable from consumer attitudes and intentions (Rubik and Frankl 2005). Practically, awareness and understanding can be evaluated more easily than behavior—through consumer surveys (US EPA 1994). Surveys have been used, for example, to determine the effect of the original US Energy Guide label on consumer awareness (Dyer and Maronick 1988). A more recent example is the research commissioned by the US Association of Home Appliance Manufacturers (AHAM 2006). Also, the FTC recently proposed an evaluation of label perception and comprehension through survey research (Federal Trade Commission 2006).

At the macro-level, one can analyze time series of shipment-weighted average efficiencies in the market, and the temporal introduction and change of labeling programs. Given that labeling programs normally coexist with energy efficiency standards, it is difficult and costly to analytically separate the impact of one from the other (du Pont, Schwengels et al. 2005). Further problems arise when the analyst tries to discriminate between those two impacts and the effect of structural change in the

appliance market (Wiel 2005). Finally, in any macro-level evaluation, it remains unclear how much of an observed effect in the market is attributable to the label itself. For example, the evaluators of the European Union's appliance labeling program caution that it is difficult to separate labeling from other activities, such as the promotion of more energy-efficient appliances through retailers, as well as retail personnel better trained with respect to energy efficiency issues (Bertoldi 1999).

2.5.2 Experimental research on antecedent strategies

Since studies on the micro-effect of labeling on consumer behavior are in short supply (Bjorner, Hansen et al. 2004, 412; Sammer and Wüstenhagen 2006, 187), it is worth looking at psychological experimental research on antecedent strategies—that occur *before* an intended behavior—such as information programs more generally, before focusing on label experiments with monetary information in particular.

Shippee (1980) reviewed field experiments on the effectiveness of providing energy information. Only minimal or non-significant reductions in electricity consumption could be shown for treatment groups that received the information, relative to the control group, or relative to pre-information conditions.

Ester and Winett (1982) evaluated antecedent experiments from different areas of resource management, including residential energy conservation. In many cases, they found no effects or, at most, minimal effects. Effectiveness was somewhat higher when information was specific and when the study design considered proximity, convenience, and salience of the requested behavior.

Katzev and Johnson (1987) provided a comprehensive review of energy-related

experiments, almost all of which shared the following characteristics: the random assignment of a small group of volunteers into treatment and control groups; an explicit invitation to conserve energy; the measuring of energy consumption before, during, and after the experiment; and the use of standard statistical tests for impact assessment. Overall, the evidence on the impact of antecedent strategies was inconclusive. Only little effect, if any, on energy consumption could be found for antecedent strategies.

The reviews cited above caution that, in general, simply providing information may not be as effective as often thought.

2.5.3 Experimental research on labels with monetary information

Few experiments explicitly contrast physical and monetary information. The three journal articles cited below, about LCC disclosure for household appliances, show mixed results regarding the impact of different treatments on consumer behavior. Their results are summarized in table 4 below.

McNeill and Wilkie (1979) conducted a series of experimental tasks with respect to providing energy information. Most of the tasks are not described here because this dissertation focuses on consumer choice, not on communication or learning. In the final experimental task, which was deemed closest to real shopping behavior, consumers were asked to hypothetically build their own refrigerators by choosing from different available features, such as size and defrost type. No significant effect could be detected for this final task. The 155 study participants—all females—were intended to represent a cross-section of the population of the Gainesville, Florida area. The study was not conducted in a field setting, and most participants were not intending to buy a refrigerator at the time.

Moreover, participants needed to remember a given feature's energy performance from the preceding experimental task because no additional energy use information was supplied. The researchers applied six distinct treatment conditions, varying with the presence of energy-use data, the presence of comparative energy-use information, the unit of measurement, the time period under consideration, and the degree of disclosure. Differences in information format did not lead to consistent differences in energy use. Making energy-use information available led to a 2.3% decrease in energy use, relative to the control group; however, that was not a statistically significant difference. Changing the information format from kilowatt-hours to dollars did not lead to statistically significant differences between treatment groups either (McNeill and Wilkie 1979).

Hutton and Wilkie (1980) examined the effect of life-cycle cost disclosure in a study of consumer behavior with 94 females from Gainesville, Florida. One of the tasks required participants to build their own hypothetical refrigerator models according to their individual needs. The after-only experimental design employed two experimental groups—one receiving LCC information; the other, information on dollars spent on energy per year. The control group did not receive any information about operating cost. None of the three groups received any physical energy use information. (Physical energy use information is not mentioned explicitly in the article. The authors' intention, however, was to reflect the requirements of the original Energy Guide label, which showed only monetary cost information.) LCC figures were estimated, assuming an appliance lifetime of 14 years, average energy prices, and a net discount rate of zero. The researchers justified the zero rate on the grounds that energy cost increases would compensate for discounting. Results for the refrigerator building task were as follows.

Participants who received the “energy dollars per year” treatment did not perform differently from those in the control group. Participants in the LCC treatment group constructed refrigerator models with both lower lifetime energy cost and lower LCC, relative to the control group. In two slightly different experiment settings, the average treatment effect sizes ranged from -12% to -27% for lifetime energy cost, and from -9% to -17% for LCC. Finally, the LCC group had significantly lower lifetime energy cost and lower LCC, compared with the “energy dollars per year” group. The authors concluded that life-cycle cost was a superior form of information when focusing on behavioral responses (Hutton and Wilkie 1980).

Anderson and Claxton (1982) conducted a refrigerator sales field experiment and combined the effect of label information type (kilowatt-hours/month vs. dollars/year) with sales force emphasis (no emphasis vs. emphasis). Emphasis-on-energy information included providing, in addition, the estimated 10 year operating cost and LCC data for each model. That two-by-two design encompassed four possible treatment combinations that were complemented by a control group, which did not receive any energy information. The treatment was randomly assigned across 18 stores of a major department store chain in Western Canada. Results were differentiated into a total of 569 large refrigerator sales and 119 small refrigerator sales. Within the latter category, the number of observations ranged between 16 and 26 per treatment category. Regarding large refrigerators, energy efficiency did not differ significantly among treatment conditions at a 5% level of significance. Regarding small ones, the providing of energy information improved mean energy use by 12%, relative to the control group. Yet, differences between the effects of monetary information versus physical information

were statistically insignificant. A difficulty reported by the researchers was that the “emphasis” treatment, which included providing the additional life-cycle cost information, was not performed by the store staff as planned (Anderson and Claxton 1982).

Table 4: Experiments on the effect of operating and life-cycle cost disclosure on consumer behavior

Reference	Sample	Design	Independent variables	Effect on energy ^a	Comments
(McNeil and Wilkie 1979)	155 Females from Gainesville, Florida	Experimental building task to construct hypothetical fridge-freezers	Energy-use information ^b available (vs. unavailable) Dollars (vs. kilowatt-hours) Yearly time period for computing energy consumption (vs. monthly time period) Overall product energy use (vs. energy use by each major product feature) Comparative energy-use information (vs. no comparative information)	-2.3% n/a n/a n/a n/a	Overall: <ul style="list-style-type: none"> No field setting Generalization to larger population problematic Most participants were not intending to buy an appliance Participants needed to remember a given feature's energy use from the preceding experimental task
(Hutton and Wilkie 1980)	94 Females from Gainesville, Florida	Experimental building task to construct hypothetical fridge-freezers	Yearly energy cost information (vs. no energy cost) Life-cycle cost (vs. no energy cost) Life-cycle cost (vs. yearly energy cost)	n/a -12% to -27%*** -13% to -27%***	Overall: Most limitations as above, but a given feature's energy use was provided to consumers Also: 9% to 17% lower life-cycle cost* Zero discount rate for life-cycle cost calculation Also: lower life-cycle cost**
(Anderson and Claxton 1982)	688 Customers of department stores in Western Canadian cities	Sales field experiment/subgroup of large fridges purchased Subgroup of small fridges purchased	Sales emphasis of energy information ^c (vs. no emphasis) Dollars (vs. kilowatt-hours) Energy-use information ^b available (vs. unavailable) Sales emphasis of energy information ^c (vs. no emphasis) Dollars (vs. kilowatt-hours) Energy-use information ^b available (vs. unavailable)	0.86% 1.6% 1.2% -3.1% -0.84% -12%***	Sales emphasis treatment not performed as planned Sales emphasis treatment not performed as planned

Note: *** p < 0.03; ** p < 0.05; * p < 0.10; some effects and significance levels were not reported; n/a — not available; a) Mean energy use of products chosen relative to the energy use of the experimental reference group in parentheses; b) Energy-use information encompasses both physical and monetary information; c) Sales emphasis of energy information includes the additional provision of 10-year lifetime operating cost and resulting life-cycle cost

Table 4 shows that providing energy information had no significant effect in several cases. Also, two of the three studies suggested that there was no clear superiority of monetary information over physical information (dollars vs. kilowatt-hours) when compared directly. That result stands in contrast to predictions derived from cognitive psychology, and in contrast to the consumer demands described above. Moreover, in the study by Anderson and Claxton (1982), the difference between dollars and kilowatt-hours had different signs, varying by appliance groups.

Nevertheless, the LCC study by Hutton and Wilkie (1980) exhibits significant treatment effects for LCC disclosure whose sizes are in the same range as the one detected by Anderson and Claxton (1982) in the last row. Finally, yearly energy cost information does not seem to be effective; or, it seems to be less effective than LCC disclosure.

Methodologically, two of the three studies have not been conducted in the field and relied exclusively on female participants. The third study—the sales field experiment—encountered implementation problems with the sales personnel.

Overall, no clear picture arises from prior research on the effect of information programs or the provision of monetary information on consumer behavior. That finding will be discussed in section 2.7 below.

2.6 The internet as a research tool

Over the recent years, more and more analysts have begun using the internet as a research tool. The question here is whether internet-based research can help to shed light on the causal effect of life-cycle cost disclosure on consumer behavior. This section covers

metrics for internet-based research (2.6.1) and several issues regarding the implementation and limitations of web-based experiments (2.6.2).

2.6.1 Metrics for internet-based research

Conducting internet-based research requires an understanding of internet metrics and their reliability. This section briefly reviews the relevant literature. After introducing common measures derived from server logs files, reliability issues related to the presence of robots, interruption of transmission, caching, and time measurement will be addressed.

Although the internet encompasses a variety of services such as email, telnet, file transfer protocol, etc., experiments have been conducted mostly on the world wide web (Reips 2002b, 243). Throughout this dissertation, I will therefore use the terms online experiment, internet experiment, web experiment, and web-based experiment interchangeably. The same applies for terms such as online research, internet research, web research, and web-based research unless otherwise noted.

Web-based research in general can be user-centric or site-centric. While user-centric research tracks the behavior of individuals across websites of different institutions, site-centric research focuses on the website of a single institution. Site-centric research usually relies on server log files, that is, recordings of all users' requests to a given server. Each line of a log file contains a "hit" which represents a request for a single website component, be it a block of text or an individual graphic image (Mullarkey 2004, 43-47). Besides "hits", other measures are available. Comparing the use of different websites is difficult because of competing measurements such as "click-through", "page impressions" "page views", "visitors", and "returns" (Reips 2001, 205;

Peterson 2004). Those measures that are important in the context of this dissertation will be described below at the respective necessary level of detail.

A *click-through* (or simply “*click*”) occurs when a user clicks on a particular website element, such as a link or a button. *Page views* (or *impressions*) refers to the number of pages or screens viewed by a given user—regardless of the number of individual elements on the page (Nicholas, Huntington et al. 2002, 46-47; Peterson 2004). *Visitors* refers to separately identifiable users who view web pages (Peterson 2004).

The reliability of some web metrics is problematic because of server requests by robots and spiders, interrupted requests, caching of web content, and the determining of session length.

First, it may be difficult to distinguish human internet users from “non-human user agents” (Peterson 2004, 24). Server log files track *all* activity including website requests from robots, spiders, and crawlers—software that automatically scans the internet for information. These requests have to be filtered out if a log file analysis is supposed to focus on human activity only (Mullarkey 2004, 44; Jamali, Nicholas et al. 2005, 559). Non-human user agents may be recognized and excluded from the analysis when they identify themselves as such (Nicholas and Huntington 2003, 392). Well-known robots can also be identified by their Internet Protocol address and information from the “user-agent” field. Unfortunately, the updating of blacklists for robot detection cannot keep pace with the development of new robots. Moreover, some robots mask their user information, allowing them to look like standard internet browsers. Finally, “offline browsers” that download entire websites for offline viewing may behave similarly to search engine robots, thereby complicating any differentiation (Tan and Kumar 2002).

Second, interrupted requests may be recorded as hits in the server log file. If a user requests a page, then subsequently decides to cancel the operation, the request may, nonetheless, be recorded as a hit (Mullarkey 2004, 44).

Third, caching can bias the estimating of hits. Server logs do not provide the full picture of user activity because caching can occur at different levels of the internet system. The system consists of web servers, proxy servers, and client computers. While caching on web servers can be accounted for in log file analysis, the two other forms of caching cannot be accounted for. Proxy servers are in an intermediate position between web servers and clients. They store data from web servers and allow for requests by several clients, thereby speeding up the transmission process to the end users. Proxy server caching can be turned off by the server, which is typically the case for web pages that are generated dynamically (Mullarkey 2004, 44-50; Peterson 2004, 24). In addition, some elements of a website may be stored on a user's hard disk ("local caching") so that subsequent requests for the same elements may be directed to the hard disk and not to the remote web server (Mullarkey 2004, 44-50). Such local caching is particularly relevant for backward navigation in a user's browser. Requests that are cached at the local level are not counted as hits in the sever log under consideration and cannot be adjusted for (Nicholas, Huntington et al. 2002, 71).

Fourth, time measurement is of limited value because of undetectable variance in caching, load-up time, and information density. Caching affects the number of pages recorded and the page view time. When a user's request is directed to the local cache, the server log cannot record the point of time of the operation. Subsequent requests to the server can only be compared to log entries that refer to non-cached data requests earlier

in time. Therefore, local caching leads to an upward bias of page view time. Load-up time depends on the time of the day because the number of simultaneously accessing web users influences file delivery speed. It also depends on the speed of a user's internet connection, and on the number of files downloaded. The greater the information density of a given web page, the longer it takes to download the page (Nicholas, Huntington et al. 2002, 67-71).

Fifth, the duration of a session cannot be provided exactly because, technically, users log on, but they do not log off. Consequently, the log file does not contain any log-off entries. Instead, user inactivity is used as a proxy measure. If a user does not request any web data for a specified period of time, the server automatically terminates the session (Nicholas, Huntington et al. 2002, 64).

2.6.2 Implementation and limitations of web-based experiments

Technical options for implementing online experiments must consider certain advantages and disadvantages.

Generally, online experiments can be implemented using either server-side or client-side programming. While client-side programs run on users' computers, server-side programs run on the remote machine that the user accesses over the internet; that is, a server. Server-side programming does not require a special computer system or browser, and therefore ensures that the experiment will be visible on the screens of all internet users.

Client-side programs, on the other hand, can run with JavaScript or Java—computer languages that are freely available to users and programmers. Since they are

executed on the client's computer, they do not require much of the server's capacity. A potential disadvantage is that they can run properly only if the user's browser is allowed to execute those kinds of programs (Reips 2002b, 248; Birnbaum 2004, 807-808).

Client-side programs may introduce platform-dependent biases when certain users allow program execution but others do not. Vice versa, the use of certain technologies may indicate something special about a given user. For example, a study by Buchanan and Reips demonstrated that Macintosh users reached higher scores on an "openness" scale, and that the average education of users who allowed JavaScript programs to be executed was lower than that of those who did not allow JavaScript (Buchanan and Reips 2001). Therefore, to prevent bias from self-selection, Reips recommends using the "most basic and widely available technology" for conducting web-based experiments (Reips 2002b, 248). On the other hand, already in 2004, Birnbaum diagnosed that "one now expects to find JavaScript and Java on most users' machines" (Birnbaum 2004, 808).

In principle, client-side programs should produce the same output, regardless of computer systems and browsers. That ideal, however, cannot always be achieved, given the large variety in existing hardware and software (Reips 2002a, 246). Birnbaum therefore recommends testing new client-side programs with the major computer systems, browsers, and browser versions in use (Birnbaum 2004, 809).

An important challenge in web-based experiments is the possibility of receiving multiple submissions from a given participant. Multiple submissions cannot be detected unless the website "visitor" can be clearly identified (Peterson 2004, 50).

Generally, several remedies for multiple submissions are available if users are actually told about the experiment and if personal user information can be gathered. If

they do not know about the experiment, however, the available options are reduced.

One option is to ascertain whether several submissions came from computers with the same internet protocol (IP) address. Today, unfortunately, many IP addresses are assigned dynamically. In such a system, whenever a new user logs on, the provider may assign a new IP address (Birnbaum 2004, 814). In the context of using IP addresses for identification, several scenarios are conceivable in which 1) a person participates more than once by using the same computer or IP address, 2) a person participates more than once by using different computers, 3) different persons participate, using the same computer, 4) multiple datasets with different IP addresses come from the same computer, and 5) multiple datasets come from different computers but have the same IP address assigned from proxy servers—either for all the webpages or for individual page elements (Reips 2002b, 250).

Alternatively, one can use *cookies* to determine whether a user has previously participated in the experiment. A cookie is an identification number that is stored on a participant's computer (Birnbaum 2004, 815). Some researchers deem placing cookies unreliable because they are considered problematic by many users (Nicholas, Huntington et al. 2002, 67) and "will exclude a large portion of participants" from the experiment (Reips 2002b, 251). Yet, contrary empirical findings do exist. In one study, users were randomly assigned to either a cookie or a non-cookie treatment. The treatment had no effect ($p=0.271$) on the number of pages requested by participants (Drèze and Zufryden 1998, 16). Nevertheless, the experimenter cannot know whether a user has previously participated using another computer, or whether he or she has deleted the cookie. Both cases allow for multiple submissions that cannot be controlled (Birnbaum 2004, 815). In

addition, by using cookies, one cannot detect when different users have accessed the website with the same computer; that is, with the same cookie (Drèze and Zufryden 1998, 15).

Another problem is that stimulus delivery over the internet cannot be fully controlled. Even if the experiment can run on the client computer, the stimulus designed by the experimenter may be received differently by users, given the variety in existing software, computers, monitors, and speakers. For example, color displays may vary between systems. That is true even for so-called "Web-safe colors" (Birnbaum 2004, 812) that were supposed to be the same on every system. Since individuals quickly adapt to fixed background conditions, and since perception by the same individual is constant, variation in perception between users can be disregarded in many cases (Birnbaum 2004, 811-812).

The dropout of experiment participants may bias results. A dropout is a user who begins participating in a given experiment, but leaves before completing it. Dropout seriously threatens internal validity in between-subject experiments because it can lead to false results, even if experimental conditions have been randomly assigned and the dropout rates of both the control group and the treatment group are the same (Birnbaum 2004, 816-817).

Recruitment for web-based experiments cannot be fully controlled if it is done passively. "Passive" implies that one simply lets users find the experimental website through search engines or hyperlinks. Given the internet's dynamic nature, one cannot predict or control how hyperlinks will develop in the future. Depending on which other websites published link to the experiment, different kinds of users may click through to

participate. Given the dynamic nature of the internet, it would be unrealistic to aim for a sample that represented a stable population of web users as such. Regardless of the chosen recruitment technique, the obtained sample might not be representative of a particular population because of potential self-selection problems (Birnbaum 2004, 818-820).

Response bias may occur, depending on the choice of input devices, such as check boxes, pull-down selection lists, or the size of text boxes (Birnbaum 2004, 821-822).

Experimenter bias is not a major concern because web-based experiments can be highly standardized. Moreover, they can be documented so that they can be easily replicated (Birnbaum 2004, 822).

Finally, web-based experiments may involve technical configuration errors—such as uncontrolled open access to unprotected experimental directories, disclosure of confidential participant data through internet addresses, and revelation of the experiment structure through file and folder titles (Reips 2002a, 241-247).

The last two sections have shown a variety of limitations inherent in web-based research and experimenting. Those that are relevant to this dissertation are discussed in chapters three and four.

2.7 Discussion

A review of the literature has shown a mismatch among suggestions derived from theory, empirical findings, and activities in the policy community with respect to life-cycle cost disclosure. Theory suggests that more information is helpful to consumers, and that

providing monetary information may help reduce consumers' cognitive efforts. The few experimental studies that contrast physical and monetary information, however, provide only ambiguous hints as to whether life-cycle cost disclosure is really effective. Finally, despite the lack of clear evidence regarding its effectiveness, life-cycle cost disclosure is currently being used on many energy efficiency websites or being discussed in the context of conventional labeling.

Putting those findings into perspective requires a broader look at current research on environment-related information programs. Open questions for future research include, how consumers demand and use information, how success of information provision programs can be measured, how information is related to real action, and how information technology can be effectively used for information programs (Wilbanks and Stern 2002, 341-346). Brewer et al. suggest studying how messages should be designed to suit audiences' attention patterns and cognitive capacities, as well as looking at intermediary groups that try to provide information to consumers (Brewer and Stern 2005, 74-76).

Such research needs call for an appropriate form of evaluation of the effectiveness of life-cycle cost disclosure. All evaluations have to deal with the counterfactual problem, or the "fundamental problem of causal inference" —that one cannot observe a unit that is treated and, at the same time, not treated (Holland 1986, 947). When feasible and implemented correctly, randomized experiments represent the best approach to creating a counterfactual and to evaluating treatment effects (Rossi, Freeman et al. 1999; Harrison and List 2004). Still, randomization can be applied in different settings. The experiments about monetary cost disclosure described in section 2.5.3 were hypothetical. That is, the

participants were not intending to buy anything, or, they were susceptible to experimenter effects—introduced, for example, by the sales staff.

One way of handling both issues is to conduct field experiments on the internet in which the participants will not know that they are in the experiment. In web-based experiments, consumer behavior can be tracked unobtrusively by evaluating consumers' click-stream data, as stored in server log files (Hofacker and Murphy 2005, 239). Moreover, conducting field experiments in a commercial context motivates participants, circumventing the problem of inadequate financial incentives (Hertwig and Ortmann 2001).

Although that kind of research in conjunction with actual companies is still rare, click-stream data from field experiments has been used. For example, Murphy, Hofacker, and Bennett (2001) randomly assigned website visitors to four different websites and measured the effect on click-through behavior. In a more recent experiment, Moe (2006) conducted a field experiment about the timing of pop-up promotions on a high-traffic information website.

Of course, a web-based experiment cannot aim at creating the same environment that exists in an actual store. Nevertheless, it can serve as a kind of yardstick as to what effect size can be possibly expected from life-cycle cost disclosure in physical stores. Concentrating on appliances and cost figures purifies the results from experimenter effects that physical experiments usually have to deal with. Unlike simulated laboratory experiments, web-based experiments offer real incentives to consumers who are actually intending to buy an appliance.

Finally, the results from web-based experiments cannot be generalized to the

entire population as long as only a subset of the population uses the internet. Still, such experiments may considerably expand our knowledge about the effects of life-cycle cost disclosure. Moreover, with an increasing market share of direct online sales, the results from internet field experiments play an increasingly important role.

Those considerations were the basis for developing and implementing the two online field experiments that are described in the following two chapters.

Chapter 3: Experimental online price comparison

3.1 Introduction

The overarching question of this dissertation is whether life-cycle cost disclosure makes online-shoppers opt for more energy-efficient household appliances. To answer it, I implemented a randomized field experiment in a price comparison engine (shopbot), and in an online shop. The following sections contain the data description (3.2), the hypotheses (3.3), the research methods (3.4), and the results (3.5) for the shopbot. In section 3.6, I discuss the limitations of the shopbot experiment. An analogous presentation of the online shop experiment can be found in chapter 4.

3.2 Data

The experimental data for cooling appliances stems from a shopbot that is integrated into *WEB.DE*, one of Germany's largest internet portals (www.web.de) that was established in 1995. A recent market study estimated that WEB.DE had 10.5 million "unique users" in an average month and ranged third overall as a vehicle for advertising (AGOF 2006). WEB.DE offers a mix of information, entertainment and price comparison shopping.

Price comparison shopping can be started by clicking on, and navigating between listed product categories and products. Alternatively, users can type a specific term directly into a search field. Only navigational click-stream data, however, was collected for this experiment. Figure 5 in appendix I depicts the introductory shopping page at the WEB.DE portal.

Technically, the shopbot is operated by *Mentasys*, a Germany-based software

company that provides the technology and the underlying database with product data from manufacturers. Energy-efficiency information in the database is consistent with the requirements of the EU appliance labeling directive (EC 1994; EC 2003). Based on this data, the shopbot allows for a comparison of individual product offers from final online retailers. Retailers can access the system and provide the current prices of the products they are offering. Over time, the range of products offered and associated product prices are therefore subject to change.

Mentasys collected users' click-stream data for refrigerators, fridge-freezers, and freezers in the form of server log files. Chest freezers—although also available through the shopbot—were not part of the experiment given a low level of related click-throughs and relatively high implementation cost. Incomplete data was recorded in a separate log file. Potential reasons for incomplete data encompassed expired server sessions, technical server change due to server breakdown, and the rejection of session cookies by internet users.

Mentasys also automatically identified and removed hits from non-human user agents with the aid of available blacklists for Internet Protocol addresses and user-agent information, and provided the resulting log files. Each line in the log file contained information about a given product that was shown to, or clicked on by a user. Each click-through was associated with a specific online merchant. Table 83 in appendix V gives an abridged example of the log file format.

Additional data regarding gasoline prices for the time period of the experiment was obtained from the Association of the German Petroleum Industry (MWV 2006).

The subsequent data preparation comprehended the removal of data from invalid

days, and the removal of remaining hits from non-human user agents. Days are referred to as invalid for those days on which the experimental set up deviated from the agreed layout due to unforeseen software problems. Due to proprietary considerations, these days are not revealed in detail here. Hits from non-human user agents were identified through the keywords “bot”, “crawl” “spider” or “mail”, respectively, in the user-agent string of the log file. No click-through was recorded for any of these agents.

3.3 Hypotheses

With the data from WEB.DE, I want to test the following hypothesis:

H_{1a}: “The disclosure of life-cycle cost does not make online shoppers opt for household appliances that are different in terms of their energy efficiency.”

H_{1b}: “The disclosure of life-cycle cost makes online shoppers opt for household appliances that are different in terms of their energy efficiency.”

The hypotheses are nondirectional—implying a two-tailed test—because of the ambiguity of prior research findings. Although I do expect that the provision of life-cycle cost will lead to higher mean energy efficiency, I cannot *a priori* exclude the possibility that the information disclosure may instead lower it.

This possibility requires a closer look at prior research. As described in section 2.5, the empirical evidence regarding the effectiveness of information programs in general, and monetary cost disclosure in particular is ambiguous. Nevertheless, none of the experimental research closely related to life-cycle cost disclosure suggests that monetary information provision may in fact lead consumers to systematically buy less energy-efficient products. The problem becomes more difficult when broadening the

perspective to the larger body of research on decision support systems (Scott Morton 1984, 14-16). Here, a small number of experiments from the early 1980s are reported in which users of decision support systems actually performed worse than the control group (Sharda, Barr et al. 1988, 140-145). Nevertheless, a recent study of two decision support systems on the internet that comes closest to the proposed experiment reports an improvement in both decision quality and a reduction in decision effort (Häubl and Trifts 2000). All in all, a two-tailed test seems to be more appropriate.

A question closely related to energy use is whether life-cycle cost disclosure actually changes the estimated life-cycle cost in the treatment group:

H_{2a}: “The disclosure of life-cycle cost does not make online shoppers opt for household appliances that are different in terms of their estimated life-cycle cost.”

H_{2b}: “The disclosure of life-cycle cost makes online shoppers opt for household appliances that are different in terms of their estimated life-cycle cost.”

A third pair of hypotheses refers to the economic effect of life-cycle cost for the providing website. Since the business model of the shopbot relies on generating click-throughs to final retailers, the total number of clicks is of crucial importance:

H_{3a}: “The disclosure of life-cycle cost does not change the number of click-throughs to final retailers.”

H_{3b}: “The disclosure of life-cycle cost changes the number of click-throughs to final retailers.”

These hypotheses are non-directional, too, because on the one hand, life-cycle cost disclosure may make the information more helpful and convincing. On the other hand, it may make information load larger and more cognitively demanding so that consumers

like the interface less than consumers in the control group (Chiang, Dholakia et al. 2005).

3.4 Method

In this section, I describe the experimental research design (3.4.1), the treatment (3.4.2), the procedure that participants followed (3.4.3), the chosen measures (3.4.4), and the regression models I applied (3.4.5).

3.4.1 Design

All experiments described in this dissertation are two-group posttest-only randomized experiments (Trochim 2004) with cross-sectional data from different internet users. The control group always received the regular product price information, whereas the treatment group was, in addition, offered information about estimated operating and life-cycle cost.

3.4.2 Treatment

The treatment encompasses the display and calculation of cost (3.4.2.1), the display of usage assumptions and their adjustment (3.4.2.2), the default assumptions for prices and preferences (3.4.2.3) and the technical implementation of the treatment (3.4.2.4).

3.4.2.1 Display and calculation of life-cycle cost







Different from the control group, the treatment group was offered additional operating and life-cycle costs. On most web pages, the treatment group saw an equation in the following format:

$$\textit{Life-cycle cost} = \textit{purchase price} + \textit{operating cost}$$

These costs were provided for each product. On certain web pages, individual cost components were provided separately. A full documentation of all relevant web pages and cost formats is provided in appendix I.

While the control group received the same information in both rounds, the treatment group was shown two distinct treatments in two separate experimental rounds. These rounds differed with respect to the underlying assumptions, the calculation of operating cost, and the presentation of life-cycle cost. Table 5 exhibits all experimental conditions for a sample refrigerator. Each figure in the table represents a basic building block of which longer product listings on the experimental web pages consisted.

Table 5: Experimental conditions in the main product listing of the shopbot

<i>Experimental condition and default assumptions</i>	<i>Visual stimuli for sample refrigerator</i>										
Control	 <p>Bauknecht KVA 1501 weiss 199,00 € bei baur.de </p> <p>Kühlschrank 117l 223kWh/Jahr Effizienzklasse A gesamter Nutzinhalt: 117 l · Bauarten: Standgerät... mehr Jetzt 10 Angebote im Preisvergleich oder bei ebay.</p>										
<p>Treatment round 1</p> <ul style="list-style-type: none"> • <i>Time horizon:</i> 5 years • <i>Price of electricity:</i> 0.16 € / kWh 	 <p>Bauknecht KVA 1501 weiss Gesamtkosten = Preis + Betriebskosten 377,40 € = 199,00 € + 178,40 €</p> <p>bei baur.de </p> <p>Kühlschrank 117l 223kWh/Jahr Effizienzklasse A gesamter Nutzinhalt: 117 l · Bauarten: Standgerät... mehr Jetzt 10 Angebote im Preisvergleich oder bei ebay.</p>										
<p>Treatment round 2</p> <ul style="list-style-type: none"> • <i>Time horizon:</i> 9 years • <i>Price of electricity:</i> 0.16 € / kWh 	 <p>Bauknecht KVA 1501 weiss 199,00 € bei baur.de </p> <div style="border: 1px solid black; padding: 5px;"> <p>Betriebskosten geschätzt für 9,0 Jahre</p> <table> <tr> <td>Gesamtkosten</td> <td>=</td> <td>Preis</td> <td>+</td> <td>Betriebskosten</td> </tr> <tr> <td>520,12 €</td> <td>=</td> <td>199,00 €</td> <td>+</td> <td>321,12 €</td> </tr> </table> </div> <p>Kühlschrank 117l 223kWh/Jahr Effizienzklasse A gesamter Nutzinhalt: 117 l · Bauarten: Standgerät... mehr Jetzt 10 Angebote im Preisvergleich oder bei ebay.</p>	Gesamtkosten	=	Preis	+	Betriebskosten	520,12 €	=	199,00 €	+	321,12 €
Gesamtkosten	=	Preis	+	Betriebskosten							
520,12 €	=	199,00 €	+	321,12 €							

In each experimental condition, the first line shows the refrigerator model. It is followed by price information, and cost information, where applicable. The price information refers to a specific final retailer (here: “baur.de”). Operating cost can be adjusted by clicking on “Betriebskosten”. The before-last paragraph contains basic product characteristics regarding capacity, energy use, energy efficiency class, total

capacity, and refrigerator type. The last line indicates the number of alternative retailers that offer the same product.

Life-cycle cost (LCC) is estimated based on the following formula:

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

where P = appliance purchase price [€], C_t = yearly operating cost [€/year], N = chosen time horizon [years], and r = discount rate.

For continuously working cooling appliances, operating costs are calculated as

$$C_t = P_E * C_E$$

where P_E = price of electricity [€/kWh], and C_E = consumption of energy [kWh/year]. C_E is provided as EU energy label information (EC 1994; EC 2003). P_E was held constant over time, and consumers were told explicitly about the static character of the estimation (see figure 2 in the next section).

This simplification disregards shipping, installation, and maintenance cost, which is consistent with what most of the energy efficiency websites reviewed in chapter 2 present. As long as these additional costs do not vary systematically by appliance efficiency, it does not matter when comparing different models (McMahon, McNeil et al. 2005, 160).

By means of the additional life-cycle cost information, users in the treatment group were also able to sort and filter appliances by life-cycle cost.

3.4.2.2 Display of usage assumptions and their adjustment

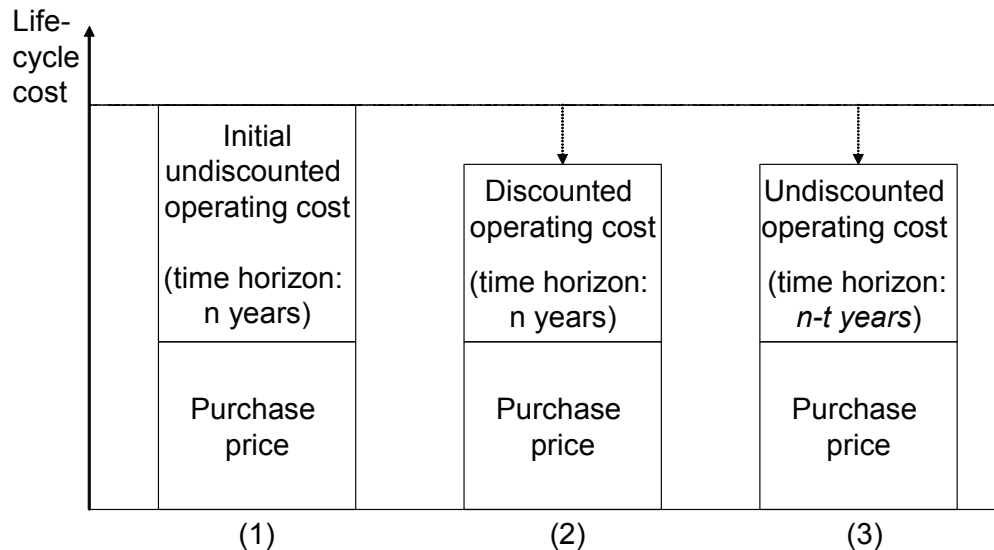
The treatment group was able to actively adjust the usage assumptions that underlie the

life-cycle cost estimation. For presenting the present value of future operating cost to consumers, I considered two alternative forms of discounting. After pre-testing *direct* discounting, I eventually settled for *indirect* discounting.

Direct discounting could have potentially been implemented by asking explicitly for a user's individual discount rate, or, alternatively by offering "choice tasks", "matching tasks", "rating tasks", or "price tasks" (Frederick, Loewenstein et al. 2002) as described in section 2.4.4.3. Mentasys, the implementing company, pre-tested the first option and asked users explicitly about their discount rate in a test version of the experimental price comparison. The resulting feedback, however, indicated a lack of comprehension and usability. Therefore, direct discounting was abandoned, and indirect discounting was used for the rest of the project.

At its core, the notion of indirect discounting put forward here implies that undiscounted operating cost can be reduced in two alternative ways. Figure 1 shows how undiscounted operating cost (1) can be reduced by means of direct discounting (2) or by reducing the underlying time horizon (3).

Figure 1: Indirect discounting with an equivalent reduction in time horizon



Different from conventional direct discounting (2), the here proposed alternative relies on a calculatory shortening of the underlying time horizon (3). In principle, the effect is the same: the estimated initial operating costs get reduced. This does not mean that the actual physical lifetime of a given appliance cannot be longer than the specified time horizon. A reduction in the reference time horizon simply changes the measuring rod regarding the relative cost-effectiveness for a list of appliances. In this way, indirect discounting (3) can substitute for direct discounting (2).

Practically, consumers therefore only had to specify a reference time horizon for the estimation of operating cost, but no discount rate at all, as shown in figure 2:

Figure 2: Adjustment of assumptions in the shopbot's treatment group

Betriebskostenberechnung

Die Schätzung der Betriebskosten basiert auf den unten stehenden Annahmen. Diese Durchschnittswerte können Sie individuell anpassen. Mögliche zukünftige Strompreisänderungen werden nicht berücksichtigt.

Strompreis: €/kWh
Nutzungsdauer: Jahre

Die Betriebskosten werden folgendermaßen abgeschätzt:

Betriebskosten = Stromverbrauch x Nutzungsdauer x Strompreis
z.B.: 480 € = 300 kWh/Jahr x 10 Jahre x 0,16 €/kWh

Dieses Beispiel dient nur der Veranschaulichung und bezieht sich nicht auf die angezeigten Geräte.

The first paragraph in figure 2 explains that the estimation relies on adjustable assumptions (shown in the second paragraph), and that the default assumptions represent average values. It also cautions that the estimation is static in nature and that it does not reflect potential future changes in electricity prices. The three paragraphs at the bottom illustrate the estimation formula with a sample calculation and make explicitly clear that the sample calculation does not refer to any appliance currently looked at by the consumer.

3.4.2.3 Default assumptions for estimating operating cost

The estimation of operating cost for cooling appliances requires default values for the discount rate, the time horizon, and the price of electricity.

The default discount rate should in principle be rooted in empirical estimates from the literature. Unfortunately, there is no single discount rate. Instead, implicit discount rates estimated in the early 1980s for household appliances in the United States ranged from about 0% to 300%. From the most recent survey I could identify concerning hypothetical refrigerator purchasing decisions of Germans, one can infer an implicit discount rate of 18% (or less).

For the purpose of indirect discounting, this inference can be turned upside-down: given an implicit discount rate of 18% and the known average service life of household appliances in Germany, one can calculate a reduced time horizon that can substitute for direct discounting. In other words, one can determine the value of operating cost for an equivalent time horizon (ETH) that must be equal to the conventionally discounted operating cost. The general condition is given as:

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

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), this expression can be reduced to

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

Given an exogenous implicit discount rate of 18%, and a known average service life of 14.4 years for refrigerators, the equivalent time horizon equals about 5 years. Practically, in the experiment, these 5 years were presented to consumers as a default value without making any explicit reference to the concept of discounting. When

consumers adjusted the time horizon to their personal needs, they implicitly changed the discount rate. The resulting overall equation for life-cycle cost is, therefore, given as:

$$LCC = P + ETH * P_E * C_E$$

where P = appliance purchase price [€], ETH = equivalent time horizon [years], P_E = price of electricity [€/kWh], and C_E = consumption of energy [kWh/year].

One problem in setting up the experiment was the difference in known service life between refrigerators (14.4 years) and freezers (18 years) which would have required differentiated time horizons for each appliance type. Consumers, however, were able to switch between appliance types and may have assumed that the estimation of operating cost remains the same for all appliances. Therefore, I applied one common service life (14.4 years) and one derived equivalent time horizon of 5 years to all cooling appliances in the first round of the experiment.

The second treatment round represented a more normative approach to consumer decision-support. 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. Here, I chose an implicit discount rate of about 6% that was closer to the then current long-term interest rate of about 4% (Deutsche Bundesbank 2006). Since consumers may consider the investment into a cooling appliance as somewhat risky (Sutherland 1991, 81; Frederick, Loewenstein et al. 2002), the remaining difference between 4% and 6% was supposed to cover this risk premium.

All default values for cooling appliances can be seen in table 6:

Table 6: Default assumptions for estimating operating costs for cooling appliances

<i>Default assumption</i>	<i>Default value</i>	<i>Unit</i>	<i>Reference year</i>	<i>Comment (Reference)</i>
Price of electricity	0.16	€/kWh	2005	Mean value for Germany (VDEW 2005)
Service life of refrigerator	14.4	years	2004	Mean values for Germany from representative survey (GfK 2006)
Service life of freezer	18	years	2004	
Equivalent time horizon (treatment round 1)	5	years	2004	Common value for all cooling appliances based on implicit discount rate of 18% derived from (Kuckartz and Rheingans-Heintze 2004, 81)
Equivalent time horizon (treatment round 2)	9	years	2006	Common value for all cooling appliances based on implicit discount rate of about 6%; closer to then current long-term interest rate of about 4% (Deutsche Bundesbank 2006)

3.4.2.4 Technical implementation of the experiment

The technical implementation encompassed randomization and controlled separation of the two experimental groups by means of cookies and different internet addresses, as well as the use of JavaScript.

In principle, randomization in online experiments can be achieved by using a random number generator and assigning users to experimental conditions depending on the generated number. Alternatively, the two experimental conditions can be assigned on an alternating basis (Hofacker and Murphy 2005, 240). In this experiment, conditions were alternated for each newly incoming user. That is, the server processed an incoming

request for a web page by sending material for condition A, and set a cookie for future recognition of the user's initial experimental condition. Analogously, the next incoming user received material for condition B, and so on.

Two different sorts of cookies were utilized for separating the two experimental groups. If a given user's browser denied persistent cookies with an expiration date of several months later, the server tried to set a session cookie that would expire upon closure of the user's browser. As long as a user's cookie was recognizable, the server was able to assign the same initial experimental condition. If users accepted no cookies at all, experimental conditions would switch all the time. The resulting click stream was logged in a separate log file not included in the main analysis.

Depending on the experimental condition, users were directed to Uniform Resource Locators with different content. These varied in one letter ("A" or "B", respectively), as shown in table 7.

Table 7: Sample Uniform Resource Locators for the shopbot

<i>Experimental condition</i>	<i>URL</i>
Control group	http://shopping.web.de/web_de_powerprice_B/preischeck/kuehlschraenke-c_1222-0011.html?c=1222&__URL_NAME_S__=kuehlschraenke&fwd=1&mc=hp%40i_shopping%40boxol%40textlink3.shop%40preisvergleich
Treatment group	http://shopping.web.de/web_de_powerprice_A/preischeck/kuehlschraenke-c_1222-0011.html?c=1222&__URL_NAME_S__=kuehlschraenke&fwd=1&mc=hp%40i_shopping%40boxol%40textlink3.shop%40preisvergleich

The success of the random assignment was checked by regressing the treatment

dummy variable on user characteristics and testing the null hypothesis that all coefficients were zero (Stock and Watson 2003, 390). Since users participated anonymously in the experiment, the only user characteristics available were those transmitted to the server as part of the user-agent variable. From this variable, I extracted information regarding browser and operating system. Additional user characteristics were available through the information about previously visited websites contained in the “referrer” string. I differentiated users coming from Google, from German websites (.de), Austrian websites (.at), and Swiss websites (.ch).

Finally, full delivery of visual stimuli in the treatment group required that users had JavaScript activated on their computers.

3.4.3 Procedure

In order to assure realistic conditions for this field experiment, data was collected without obtaining participants’ informed consent prior to participation. This procedure had been approved by the University of Maryland’s Institutional Review Board (Application No. 01591).

The figures referred to in this section can all be found in appendix I unless otherwise noted. Figure 4 illustrates the experimental process. After arriving at the homepage of the web portal, consumers started the price comparison engine. The introductory price comparison page can be seen in figure 5. From this page, users could enter the experiment in two different ways. They could either move along the following path: “household appliances”> “cooling appliances” > “freezers” (or “fridge-freezers” or “refrigerators”, respectively). This path is illustrated in figure 6 and figure 7.

Alternatively, they could click directly on “refrigerators” (see figure 5) to reach a product list of different refrigerators. Due to layout restrictions of the website, this direct path was available only for refrigerators, and not for the two other appliance types.

Random assignment occurred before users could see the price comparison for the first time. Operating and life-cycle cost for the treatment group were estimated based on default usage assumptions as listed in table 6. Treatment round one had a default time horizon of five years, and treatment round two a default time horizon of nine years.

In both experimental groups, the default sorting of products was by popularity. This is illustrated in figure 7 (control) and figure 8 (treatment). The order in which hyperlinks to final retailers occurred in those product listing was determined through an algorithm which was independent of the experimental condition. Instead, the algorithm is a function of the percentage of past click-throughs to a given retailer, his specified marketing budget, and cost per click-through.

Users in both groups could sort the product listing by purchase price, and product name. Also, they could filter products by manufacturer, price range, capacity, energy efficiency class, and type. In addition, users in the treatment group could adjust the underlying assumptions for the calculation of operating costs (see figure 2 in 3.4.2.2), sort the product listing by life-cycle cost, and filter products within a specified range of life-cycle cost. Figure 10 depicts a product listing for refrigerators with a capacity greater or equal to 200 liters that is sorted by life-cycle cost.

Furthermore, both experimental groups could choose to see an in-depth comparison with detailed product characteristics in matrix format. The matrix for the treatment group consisted of two additional lines showing minimum and maximum life-

cycle cost respectively (figure 11).

Finally, users in both experimental groups could focus on a given product and move on to a price comparison of final retailers for the one product under consideration. This listing provided additional information from individual retailers, for example with respect to delivery time and shipping cost. Users could sort the listing by delivery time, product price, and retailer name. In the treatment group, users additionally received life-cycle cost estimates (figure 9).

At several steps in the process could users click-through to the website of a final online retailer whose product offer appeared in a newly opened browser window. The original browser window showing the experimental shopbot remained the same as before.

3.4.4 Measures

Measures included several dependent and independent variables. Most variables referred to products for which users had clicked-through to a final retailer, and this kind of clicking-through was possible at several stages in the process. One of these possibilities stood out regarding its lack of related purchase price information. Different from other hyperlinks, the links to *Ebay* (e.g. in figure 7 or figure 9) had no visible price tag associated. That is, neither *Ebay*'s purchase price nor related life-cycle cost was easily comparable before a click-through occurred. Therefore, the relatively small number of clicks to *Ebay* was discarded.

The dependent variable of primary interest was the standardized yearly energy consumption of those cooling appliances for which users had clicked-through to a final retailer.

Further dependent variables were the total number of click-throughs per user, as well as life-cycle cost. Since 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 default assumptions about price and time horizon. All dependent variables of interest are shown in table 8.

Table 8: Key dependent variables in the shopbot experiment

<i>Dependent variable</i>	<i>Meaning / Comment</i>
energy	Energy use of appliance [kWh/year]
lccost	Estimated life-cycle cost of appliance [€], simulated for control group based on default assumptions
ct count	Count of click-throughs per user

While potential independent variables abounded, only few of them were consistently available for a sufficiently large number of observations. These included the capacity, price, energy efficiency class, brand, and merchant of a given appliance. They are shown in table 9.

Table 9: Key independent variables in the shopbot experiment

<i>Independent variable</i>	<i>Meaning</i>
treatment	Treatment dummy variable
category	Cooling appliance category dummy variables
price	Appliance price [€]
capacity	Total capacity of the appliance [L]
efficiency class	Energy efficiency class (A - F) dummy variables
merchant	Final retailer dummy variables
brands	Appliance brand dummy variables
cookie	Cookie type (persistent/session cookie)
firefox, msie, opera, mac	Browser dummy variables (extracted from user-agent)

3.4.5 Models

For testing hypothesis H_{1a}—that the energy-efficiency of chosen products is unaffected by the treatment—I used the following regression model:

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

where *energy* = energy use [kWh/year] for cooling appliance *i*, *treatment* = treatment dummy variable, *Z* = vector of covariates (see below), and *u* = error term. This basic model was estimated for the three distinct categories “refrigerators”, “fridge-freezers”, and “freezers”. In addition, I also employed a logarithmic specification:

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

This form of the model implied that life-cycle cost disclosure would lead to a constant percentage change in energy use. Both models were also estimated for life-cycle cost as the dependent variable. All of these models were estimated with ordinary least squares.

Potential covariates were integrated into the models where appropriate. In principle, adding independent variables may explain more variance and estimate the treatment effect more efficiently (Neter and Wasserman 1974, 686; Stock and Watson 2003, 384). The addition of covariates assumes “conditional mean independence” (Stock and Watson 2003, 420) which requires that the treatment be not correlated with other independent variables. This is true for pre-treatment characteristics that are not influenced by the treatment (Neter and Wasserman 1974, 688). Given these restrictions, I only included those covariates in the regression that were not correlated with the treatment

variable. The ordinary least squares coefficients of the covariates are generally not consistent—different from the coefficient of the randomly assigned treatment (Stock and Watson 2003, 383).

As a special case, the vector of covariates Z included interactions between appliance capacity and the treatment dummy. This specification covered the possibility that the treatment effect might vary. Since consumers may—depending on appliance size—deem efficiency more or less important, the size of the treatment effect may depend on appliance capacity.

For investigating the hypothesis H_{3a} that the treatment does not change online shoppers' number of click-throughs to final retailers, I relied on chi-square tests of statistical independence and 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. The range of potential covariates is greatly reduced here because $CTCOUNT$ refers to a sum of click-throughs. While each click-through refers to individual product characteristics, the *sum* of click-throughs can only be associated with characteristics that are stable over time and do not change with every click, such as browsers.

3.5 Results

Results from the shopbot experiment are differentiated by treatment rounds and appliance categories. Section 3.5.1 presents results from the first treatment round with an underlying time horizon of five years, and section 3.5.2 those from the second treatment

round with a time horizon of nine years. All results are discussed in section 3.6.

3.5.1 First treatment round

The quality of the results reported below depends on stimulus delivery, successful randomization, cookie acceptance, and the handling of problematic clicking behavior.

Stimulus delivery did not always work as planned due to unexpected software system behavior. Therefore, I discarded click-throughs recorded during the periods of incomplete treatment implementation. See figure 27 in appendix V for the remaining click-throughs over time.

Randomization worked correctly when looking at all users visiting the experimental website. The distribution of those users who actually clicked-through to final retailers, however, was not as equalized (see table 84 in appendix V).

Persistent cookies were accepted by more than 95% of all users in treatment round one (see table 85 in appendix V). The rate of session cookie rejection could not be determined because these sessions were indistinguishable from other incomplete data due to expired server sessions or technical server change.

I considered two forms of clicking behavior as problematic. First, if users clicked on hyperlinks to the same retailer for exactly the same product in succession, I assumed impatience and disregarded the second click-through. Second, a user with a suspiciously high number of clicks—which looked like the behavior of a non-human user agent—made me discard his data entirely. I chose 20 click-throughs as the cut-off point so that I had to discard the click-throughs from six users (see table 87 in the appendix). Overall, I discarded 355 clicks. Given that any unidentified clicks from non-human user agents may

have biased the analysis, I performed the following robustness check with the remaining click-throughs: for energy use as the dependent variable, I ran regressions for all remaining click-throughs, and in addition, for each user's *final* click-through. In this way, each user's influence had equal weight on the results. The results for the total of 1969 click-throughs are presented in the following sections.

Overall, nearly 3000 separately identifiable users visited the shopbot in the three experimental appliance categories. In each respective category, they were shown more than 300 different appliances from more than 25 brands sold by 30 different retailers (see table 86 in appendix V.) Appendix V provides more detailed information on the range of life-cycle cost (figure 28), energy use box plots (figure 29), energy use histograms (figure 30), energy efficiency classes (figure 31), life-cycle cost histograms (figure 32), energy versus capacity scatter plots (figure 33), and the development of the price of regular gas in Germany during the time span of the experiment (figure 35).

3.5.1.1 Freezers

Freezers' raw mean and median energy use are both lower in the treatment group than in the control group, as shown in table 10 below. For life-cycle cost, the pattern is less consistent. While the mean is lower in the control group, the median is lower in the treatment group (see table 11).

Table 10: Descriptive statistics for freezers' energy use (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	170	233.5	238.7	57.2	135.0	664.0
Treatment	144	228.5	223.0	47.4	135.0	352.0
Total	314	231.2	226.2	52.9	135.0	664.0

Note: Energy in [kWh/year].

Table 11: Descriptive statistics for freezers' life-cycle cost (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	170	607	585	242	241	1860
Treatment	144	622	577	243	241	1315
Total	314	614	580	242	241	1860

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 12 below contains regression results for the logarithm of energy and life-cycle cost as dependent variables. In no model is the treatment coefficient on its own significant at a 5% level. When controlling for other factors and allowing for an interaction between treatment and capacity in model (3), the treatment *reduces* energy use for capacities smaller than 129 liters ($p < 0.05$), and *increases* energy use for capacities greater than 128 liters. For a freezer with the median capacity of 171 liters, the treatment leads to an overall increase in energy use by 1.0% (see table 89 in appendix V for capacity quartiles for all click-throughs).

Table 12: Effect on freezers' energy use and cost (shopbot round 1)

	(1) All CT	(2) All CT	<i>ln(energy)</i> (3) All CT	(4) Final CT	(5) Final CT	<i>ln(lccost)</i> (6) All CT
treatment	-0.017 (0.025)	0.00084 (0.0085)	-0.17* (0.068)	-0.0056 (0.013)	-0.15 (0.10)	-0.039 (0.026)
treat.*ln(cap.)			0.035* (0.014)		0.029 (0.021)	
ln(capacity)		0.34*** (0.010)	0.33*** (0.011)	0.36*** (0.015)	0.35*** (0.018)	0.51*** (0.027)
constant	5.43*** (0.017)	4.34*** (0.068)	4.42*** (0.071)	4.00*** (0.11)	4.08*** (0.11)	4.18*** (0.17)
efficiency class	No	Yes	Yes	Yes	Yes	Yes
brands	No	Yes	Yes	Yes	Yes	Yes
adj. R-sq	-0.002	0.900	0.902	0.902	0.902	0.743
N	314	314	314	159	159	314

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 34 in appendix V for residual histograms.

3.5.1.2 Fridge-freezers

Fridge-freezers' mean and median energy are higher in the treatment group than in the control group (table 13). Mean life-cycle cost is lower in the treatment group than in the control group, while the opposite is true for median life-cycle costs (table 14).

Table 13: Descriptive statistics for fridge-freezers' energy use (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	288	311.6	288.0	95.8	168.0	770.0
Treatment	293	317.2	303.0	89.9	117.0	768.0
Total	581	314.4	299.3	92.8	117.0	770.0

Note: Energy in [kWh/year].

Table 14: Descriptive statistics for fridge-freezers' life-cycle cost(shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean</i> lccost	<i>Median</i> lccost	<i>SD</i> lccost	<i>Min.</i> lccost	<i>Max.</i> lccost
Control	288	883	690	592	291	4439
Treatment	293	857	727	517	122	4439
Total	581	870	698	555	122	4439

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.

Controlling for other factors reduces the standard error of the treatment coefficient (table 15). The coefficients in model (3) and (6) imply that being in the treatment group leads to a decrease in energy use and life-cycle cost by less than 3%. Yet, none of the treatment coefficients is significant at a 5% level.

Table 15: Effect on fridge-freezers' energy use and cost (shopbot round 1)

	(1) All CT	(2) All CT	<i>ln(energy)</i> (3) All CT	(4) Final CT	(5) Final CT	<i>ln(lccost)</i> (6) All CT
treatment	0.022 (0.023)	0.014 (0.017)	-0.0086 (0.0061)	-0.019 (0.038)	-0.0091 (0.011)	-0.026 (0.020)
ln(capacity)		0.68*** (0.026)	0.67*** (0.016)		0.69*** (0.033)	1.40*** (0.051)
constant	5.70*** (0.017)	1.85*** (0.15)	1.41*** (0.10)	5.73*** (0.029)	1.37*** (0.21)	-0.87** (0.32)
efficiency class	No	No	Yes	No	Yes	Yes
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	-0.000	0.477	0.940	-0.003	0.944	0.779
N	581	581	581	237	237	581

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3.

3.5.1.3 Refrigerators

While both mean and median energy use are lower in the treatment group than in the control group (table 16), the opposite is true for mean and median life-cycle cost (table 17).

Table 16: Descriptive statistics for refrigerators' energy use (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	594	186.5	179.0	79.5	84.0	525.0
Treatment	480	183.7	173.3	71.6	84.0	525.0
Total	1074	185.2	175.0	76.1	84.0	525.0

Note: Energy in [kWh/year].

Table 17: Descriptive statistics for refrigerators' life-cycle cost (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	594	626	525	325	205	2790
Treatment	480	680	585	343	210	3159
Total	1074	650	554	335	205	3159

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 18 below shows that the treatment coefficient is significant at a 1% level in model (2). Accordingly, being exposed to life-cycle cost disclosure on average reduces energy use by 4.2% when controlling for appliance capacity and energy efficiency classes. This effect, however, gets reduced by about half and does not remain significant at a 5% level when including more covariates in model (3).

Table 18: Effect on refrigerators' energy use and cost (shopbot round 1)

	(1) All CT	(2) All CT	<i>ln(energy)</i> (3) All CT	(4) Final CT	(5) Final CT	<i>ln(lccost)</i> (6) All CT
treatment	-0.0071 (0.021)	-0.042** (0.016)	-0.024 (0.015)	-0.014 (0.031)	-0.031 (0.021)	0.0053 (0.013)
ln(capacity)		0.25*** (0.027)	0.15*** (0.027)		0.17*** (0.040)	0.72*** (0.023)
constant	5.16*** (0.015)	4.00*** (0.13)	4.51*** (0.18)	5.16*** (0.021)	3.84*** (0.21)	2.54*** (0.14)
efficiency class	No	Yes	Yes	No	Yes	Yes
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	-0.001	0.479	0.573	-0.001	0.601	0.805
N	1074	1074	1074	530	530	1074

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. eeclass: energy efficiency class. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 34 in appendix V for residual histograms.

3.5.1.4 Overall energy use and life-cycle costs

This section refers to the combined click-through observations from all cooling appliances. With respect to overall energy use, both the mean and median are higher in the treatment group than in the control group (table 19). The same is true for overall life-cycle cost (table 20).

Table 19: Descriptive statistics for overall energy use (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	1052	228.3	215.0	97.4	84.0	770.0
Treatment	917	233.4	217.0	95.7	84.0	768.0
Total	1969	230.7	215.0	96.6	84.0	770.0

Note: Energy in [kWh/year].

Table 20: Descriptive statistics for overall life-cycle cost (shopbot round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	1052	693	595	422	205	4439
Treatment	917	727	638	406	122	4439
Total	1969	709	611	415	122	4439

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 21 below exhibits regressions for energy use and life-cycle cost with several covariates. When controlling for other factors, the treatment on average reduces overall energy use by 1.8% (model 2) to 3.1% (model 4). Both results are significant at a 5% level. The reduction in energy use by 2.5% in model (2) is significant at a 1% level.

Table 21: Effect on overall energy use and life-cycle cost (shopbot round 1)

	(1) All CT	(2) All CT	<i>ln(energy)</i> (3) All CT	(4) Final CT	(5) Final CT	<i>ln(lccost)</i> (6) All CT
treatment	0.024 (0.018)	-0.025** (0.0097)	-0.018* (0.0091)	-0.031* (0.014)	-0.026 (0.014)	0.0071 (0.012)
ln(capacity)		0.33*** (0.015)	0.30*** (0.013)	0.33*** (0.021)	0.31*** (0.019)	0.78*** (0.018)
constant	5.35*** (0.012)	3.95*** (0.081)	4.17*** (0.14)	4.18*** (0.12)	4.09*** (0.11)	1.98*** (0.13)
categories	No	Yes	Yes	Yes	Yes	Yes
efficiency class	No	Yes	Yes	Yes	Yes	No
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	0.000	0.706	0.744	0.703	0.741	0.683
N	1969	1969	1969	926	926	1969

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. categories: freezers, fridge-freezers, refrigerators. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 34 in appendix V for residuals.

The effect sizes (f^2) of all regressions reported above range from 0.0021 to 0.02 (see table 90 in appendix V).

3.5.1.5 Overall impact on retail volume

From a business perspective, it is the total number of click-throughs from the shopbot to final retailers that matters. Therefore, the question is whether life-cycle cost disclosure leads to a change in click-throughs. When looking at raw means in table 22 below, the number of click-throughs per user is smaller in the treatment group than in the control group (for related histograms see figure 36 in appendix V).

Table 22: Descriptive statistics for the number of clicks per user (shopbot round 1)

<i>All click-throughs</i>	<i>N</i> Users	<i>Mean</i> CT count	<i>Median</i> CT count	<i>SD</i> CT count	<i>Min.</i> CT count	<i>Max.</i> CT count
Control	1418	0.74	0	1.62	0	15
Treatment	1492	0.61	0	1.55	0	18
Total	2910	0.68	0	1.58	0	18

Note: CT: click-throughs

Moreover, a chi-square test of independence does not reveal a difference in click-throughs between the two experimental groups that is statistically significant at a 5% level ($p=0.062$ —see table 93 in appendix V).

Table 23 below shows negative binomial regression results for the number of click-throughs per user. Although all models have a poor goodness of fit, they nevertheless indicate that the treatment has a negative effect on the number of click-throughs per user. In models (1) and (2), the treatment reduces the number of click-throughs per user by about 20% when controlling for browser characteristics and appliance categories. This effect is significant at a 5% level.

Table 23: Effect on the overall number of click-throughs (shopbot round 1)

	<i>Count of click-throughs per user</i>			
	(1) All CT	(2) All CT	(3) All CT/DCT	(4) All CT/DCT
treatment	-0.19* (0.078)	-0.21** (0.077)	-0.083 (0.10)	-0.12 (0.078)
constant	-0.30*** (0.055)	-0.98*** (0.17)	-0.15* (0.061)	-0.35*** (0.065)
lnalpha constant	1.06*** (0.058)	0.97*** (0.060)	1.19*** (0.074)	1.11*** (0.053)
browsers	No	Yes	No	Yes
categories	No	Yes	No	Yes
pseudo R-sq	0.001	0.015	0.000	0.012
N	2910	2910	2910	2910

Note: Standard errors of the negative binomial regressions in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to retailer. DCT: Models 3 to 4 serve as a robustness check. They include click-throughs that were discarded in prior models such as subsequent clicks by the same user on exactly the same product, or potential clicks from robots. categories: freezers, fridge-freezers, refrigerators.

3.5.2 Second treatment round

In the second treatment round, stimulus delivery worked without problems (see figure 37 in appendix VI for click-throughs over time). Potential problems might have been due to randomization, cookie acceptance, and the handling of problematic clicking behavior.

Randomization worked well for all users, but did not result in an equalized distribution of user characteristics among all click-throughs (see table 94 in appendix VI).

Persistent cookies were accepted by more than 96% of all users in treatment round one (see table 95 in appendix VI).

Problematic clicks due to repeated clicking on the same product or due to a high total number of click-throughs amounted to 324 observations and were discarded. The cut-off point for an usually high total number of click-throughs was the same as in round

one (20 clicks—see table 97 in appendix VI).

Overall, nearly 2400 separately identifiable users visited the shopbot. In each respective appliance category, they were shown more than 250 different appliances from more than 20 brands sold by 35 different retailers (see table 96 in appendix VI).

Appendix VI provides more detailed information on the range of life-cycle cost (figure 38), energy use box plots (figure 39), energy use histograms (figure 40), energy efficiency classes (figure 41), life-cycle cost histograms (figure 42) and energy versus capacity scatterplots (figure 43).

3.5.2.1 Freezers

Freezers’ mean and median energy use are higher in the treatment group than in the control group (table 24). As to life-cycle cost, the mean is lower in the treatment group, while the median is lower in the control group (table 25).

Table 24: Descriptive statistics for freezers’ energy use (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	114	245.1	245.0	66.3	135.0	664.0
Treatment	136	248.0	261.0	66.0	135.0	664.0
Total	250	246.7	256.0	66.0	135.0	664.0

Note: Energy in [kWh/year].

Table 25: Descriptive statistics for freezers’ life-cycle cost (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	114	833	786	268	452	2285
Treatment	136	830	790	291	398	2285
Total	250	832	790	280	398	2285

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.

When controlling for other factors (table 26), energy use is higher in the treatment group, but never significant at a 5% level. Differently, the treatment decreases life-cycle cost. Still, this effect is not significant at a 5% level either.

Table 26: Effect on freezers' energy use and cost (shopbot round 2)

	(1) All CT	(2) All CT	<i>ln(energy)</i>		<i>ln(lccost)</i>	
			(3) All CT	(4) Final CT	(5) Final CT	(6) All CT
treatment	0.012 (0.032)	0.0025 (0.012)	0.0015 (0.0099)	-0.051 (0.048)	0.0044 (0.017)	-0.031 (0.019)
ln(capacity)		0.38*** (0.014)	0.37*** (0.013)		0.37*** (0.020)	0.44*** (0.024)
constant	5.47*** (0.023)	4.16*** (0.068)	3.98*** (0.063)	5.47*** (0.032)	4.12*** (0.079)	4.50*** (0.15)
efficiency class	No	Yes	Yes	No	Yes	Yes
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	-0.003	0.860	0.903	0.001	0.905	0.795
N	250	250	250	119	119	250

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 44 in appendix VI for residual histograms.

3.5.2.2 Fridge-freezers

In the fridge-freezer category, the treatment group has both higher mean and median energy use than the control group (table 27). The same holds for life-cycle cost (table 28).

Table 27: Descriptive statistics for fridge-freezers' energy use (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	187	309.7	296.0	87.5	137.0	525.0
Treatment	142	312.5	316.0	80.7	139.0	525.6
Total	329	310.9	307.0	84.5	137.0	525.6

Note: Energy in [kWh/year].

Table 28: Descriptive statistics for fridge-freezers' life-cycle cost(shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	187	1047	923	450	501	2719
Treatment	142	1131	961	599	499	4776
Total	329	1083	943	521	499	4776

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.

When controlling for other factors, none of the treatment effects on energy use or life-cycle cost is significant at a 5% level (table 29).

Table 29: Effect on fridge-freezers' energy use and cost (shopbot round 2)

	(1) All CT	(2) All CT	<i>ln(energy)</i> (3) All CT	(4) Final CT	(5) Final CT	<i>ln(lccost)</i> (6) All CT
treatment	0.014 (0.030)	0.00015 (0.0099)	0.00074 (0.0096)	-0.0059 (0.013)	0.012 (0.014)	0.017 (0.023)
ln(capacity)		0.68*** (0.024)	0.66*** (0.026)	0.69*** (0.024)	0.65*** (0.028)	1.25*** (0.061)
constant	5.70*** (0.020)	2.17*** (0.18)	2.25*** (0.16)	1.22*** (0.14)	1.94*** (0.14)	-0.26 (0.36)
efficiency class	No	Yes	Yes	Yes	Yes	Yes
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	-0.002	0.902	0.920	0.903	0.932	0.765
N	329	329	329	162	162	329

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. eclass: energy efficiency class. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3.

3.5.2.3 Refrigerators

Refrigerators had higher mean and median energy use in the treatment group than in the control group (table 30), which is also true for life-cycle cost (table 31).

Table 30: Descriptive statistics for refrigerators' energy use (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	429	207.8	168.0	113.3	84.0	525.0
Treatment	383	213.6	189.0	109.5	84.0	672.0
Total	812	210.5	177.0	111.5	84.0	672.0

Note: Energy in [kWh/year].

Table 31: Descriptive statistics for refrigerators' life-cycle cost (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	429	801	630	448	273	3237
Treatment	383	839	647	532	273	3567
Total	812	819	644	490	273	3567

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 32 presents regression results for refrigerators' energy use and life-cycle cost.

Table 32: Effect on refrigerators' energy use and cost (shopbot round 2)

	(1) All CT	(2) All CT	<i>ln(energy)</i> (3) All CT	(4) Final CT	(5) Final CT	<i>ln(lccost)</i> (6) All CT
treatment	0.034 (0.033)	0.0096 (0.020)	0.027 (0.018)	-0.023 (0.028)	0.0098 (0.025)	0.015 (0.016)
ln(capacity)		0.51*** (0.024)	0.39*** (0.031)	0.51*** (0.032)	0.41*** (0.039)	0.73*** (0.030)
constant	5.22*** (0.023)	3.03*** (0.14)	2.82*** (0.18)	2.87*** (0.16)	2.69*** (0.19)	2.60*** (0.17)
efficiency class	No	Yes	Yes	Yes	Yes	Yes
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	0.000	0.616	0.718	0.627	0.718	0.800
N	812	812	812	453	453	812

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. eeclass: energy efficiency class. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 44 in appendix VI for residual histograms.

Most treatment coefficients on energy use and life-cycle cost are positive, but none of them are significant at a 5% level.

3.5.2.4 Overall energy use and life-cycle costs

When combining the observations from all appliance categories, both mean and median energy use are higher in the treatment group than in the control group (table 33). The same is true for life-cycle cost (table 34).

Table 33: Descriptive statistics for overall energy use (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	730	239.7	219.0	109.7	84.0	664.0
Treatment	661	242.0	223.0	103.7	84.0	672.0
Total	1391	240.8	223.0	106.9	84.0	672.0

Note: Energy in [kWh/year].

Table 34: Descriptive statistics for overall life-cycle cost (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	730	869	733	438	273	3237
Treatment	661	900	771	522	273	4776
Total	1391	884	758	480	273	4776

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.

In table 35, the treatment effect is scrutinized by adding further covariates. Most treatment effects on energy use and life-cycle cost are positive, but none of them are significant at a 5% level.

Table 35: Effect on overall energy use and life-cycle cost (shopbot round 2)

	(1)	(2)	<i>ln(energy)</i>	(4)	(5)	<i>ln(lccost)</i>
	All CT	All CT	(3)	Final CT	Final CT	(6)
			All CT			All CT
treatment	0.018 (0.024)	0.0059 (0.013)	0.013 (0.011)	-0.0083 (0.018)	0.011 (0.017)	0.0074 (0.013)
ln(capacity)		0.51*** (0.017)	0.43*** (0.018)	0.51*** (0.023)	0.43*** (0.025)	0.72*** (0.020)
constant	5.38*** (0.017)	3.23*** (0.086)	3.77*** (0.15)	2.86*** (0.12)	3.54*** (0.20)	3.24*** (0.15)
categories	No	Yes	Yes	Yes	Yes	Yes
efficiency class	No	Yes	Yes	Yes	Yes	Yes
brands	No	No	Yes	No	Yes	Yes
adj. R-sq	-0.000	0.721	0.776	0.726	0.778	0.743
N	1391	1391	1391	734	734	1391

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, CT: Click-through to online retailer. categories: freezers, fridge-freezers, refrigerators. eeclss: energy efficiency class. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 44 in appendix VI for residual histograms.

3.5.2.5 Overall impact on retail volume

For the owner of the shopbot, the business-relevant question is whether life-cycle cost disclosure leads to a change in the number of click-throughs. According to table 36 below, the number of click-throughs per user is smaller in the treatment group than in the control group (for related histograms see figure 45 in appendix VI).

Table 36: Descriptive statistics for number of clicks per user (shopbot round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean</i>	<i>Median</i>	<i>SD</i>	<i>Min.</i>	<i>Max.</i>
	Users	CT count	CT count	CT count	CT count	CT count
Control	1163	0.63	0	1.32	0	14
Treatment	1194	0.55	0	1.41	0	17
Total	2357	0.59	0	1.37	0	17

Note: CT: click-throughs

A chi-square test of independence does not reveal a difference in click-throughs between the two experimental groups that is statistically significant at a 5% level ($p=0.22$ —see table 102 in appendix VI). Negative binomial regressions for the number of click-throughs per user indicate a negative effect of the treatment, but the treatment coefficient estimates are not significant at a 5% level (table 37). As in treatment round one, all of these models have a very poor goodness of fit.

Table 37: Effect on the overall number of click-throughs (shopbot round 2)

	<i>Count of click-throughs per user</i>			
	(1) All CT	(2) All CT	(3) All CT/DCT	(4) All CT/DCT
treatment	-0.13 (0.084)	-0.13 (0.084)	-0.12 (0.086)	-0.13 (0.085)
constant	-0.47*** (0.059)	-1.48*** (0.21)	-0.26*** (0.061)	-1.26*** (0.21)
lnalpha constant	0.92*** (0.071)	0.84*** (0.072)	1.10*** (0.062)	1.03*** (0.063)
browsers	No	Yes	No	Yes
categories	No	Yes	No	Yes
pseudo R-sq	0.000	0.012	0.000	0.011
N	2357	2357	2357	2357

Note: Standard errors of the negative binomial regressions in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$, CT: Click-through to retailer. DCT: Models 3 to 4 serve as a robustness check. They include click-throughs that were discarded in prior models such as subsequent clicks by the same user on exactly the same product, or potential clicks from robots. categories: freezers, fridge-freezers, refrigerators.

3.6 Discussion

In discussing the shopbot results, I will first deal with the substantive experimental outcomes (3.6.2), before addressing general issues of internal validity (3.6.3), external validity (3.6.4), measurement (3.6.5), and how I attempted to cope with them, where possible. Section 3.6.5 summarizes all threats to validity.

3.6.1 Experimental outcomes

My three research hypotheses referred to the treatment effect on energy use, estimated life-cycle cost, and click-throughs.

Effects on energy use were only detected in round one of the experiment. This may be due to the relatively smaller sample size in round two, which was about one third smaller than in round one. Moreover, layout one made it much harder for users to avoid noticing the life-cycle cost information. On the other hand, the cost figures were higher in round two due to the longer assumed time horizon. On balance, the evidence for a negative treatment effect in round one leads to the tentative hypothesis that a prolonged experiment in round two would have detected a similar effect on energy use, too.

No treatment effect on life-cycle cost could be shown in any of the two experimental rounds. This finding needs a clarification. Life-cycle costs were only simulated for the control group in the sense that they were not actually displayed. Instead, they were estimated based on appliances' energy characteristics and common default assumptions. Moreover, different from untreated users, treated users were able to adjust the underlying assumptions. Therefore, the life-cycle cost estimates in the two groups were asymmetric: based on user-adjusted assumptions (treatment) versus non-adjusted default assumptions (control).

The adjustment of assumptions in the treatment group, however, occurred in so few cases that the outcome was not sensitive to the assumptions used (default vs. user-adjusted) in estimating life-cycle cost. Adjustments are documented in table 91 (appendix V), and table 100 (appendix VI).

If consumers were trying to minimize life-cycle cost, one would expect to always find lower life-cycle cost in the treatment group than in the control group because life-cycle cost were not provided in the control group. No such pattern, however, did emerge. This finding suggests that the decrease in energy use detected in round one was associated with a compensatory increase in appliances prices. As a result, total life-cycle cost did not differ significantly between groups.

The treatment effect sizes for energy use can be deemed “small” ($f^2=0.02$) according to a scheme proposed by Cohen (1977, 413) (see table 90 in appendix V).

The overall interest of users in the disclosed life-cycle cost was very low. Not only did less than 5% of all users adjust the underlying assumptions, but also did less than 2% of them make use of the *sorting* and *filtering* features with respect to life-cycle cost (see table 92 in appendix V, and table 101 in appendix VI). Theoretically, these two features should facilitate finding the lowest life-cycle cost considerably.

The click-through rate—i.e. the best available indicator of retail volume—was decreased considerably through life-cycle cost disclosure in round one. A potential explanation is the higher cognitive cost due to increased information presented on the screen. The problem is that this effect is no longer statistically significant ($p<0.05$) if one considers previously discarded click-throughs (repeated clicks on the same product, potential robots). Since the exact business model of determining valid click-throughs cannot be described in this dissertation for proprietary information concerns, there is some uncertainty associated with this finding. In round two, I did not detect such a decrease in click-throughs. At any rate, neither a neutral nor a negative effect on click-throughs provides an incentive for private firms to adopt life-cycle cost disclosure by

themselves—even if this was beneficial regarding the detected decrease in energy use.

Finally, the outcomes of the analysis proved to be insensitive to the price of regular gas (for the price over time see figure 35 in appendix V). Including the price in its current or lagged form into the regression models led to insignificant price coefficient estimates in most cases, and did not markedly change the treatment coefficient in any case. For the sake of simplicity, these coefficient estimates are not reported explicitly.

In sum, while treatment round two of the experiment suffers from a comparably small sample size, the evidence from round one suggests two causal effects of life-cycle cost disclosure: first, a decrease in energy use by about 2.5%. And second, a decrease or non-existing effect on the number of click-throughs which makes life-cycle cost disclosure in the chosen format of round one undesirable from a business perspective. The policy implications of the experimental findings will be discussed in section 5.2.

3.6.2 Internal validity

Potential threats to internal validity have to do with the temporal precedence of the cause (Trochim 2004), the robustness of the coefficient estimates, and the comparability of the experimental groups.

3.6.2.1 Temporal precedence of the cause

Temporal precedence was guaranteed in nearly all cases. Given the experimental design, the treatment group received purchase price, operating and life-cycle cost prior to clicking through to a final retailer—with the only exception being direct links to Ebay which were lacking associated price and life-cycle cost information. Therefore, the small number of click-throughs to Ebay was not included in the analysis.

3.6.2.2 Robustness of coefficient estimates

The treatment coefficient estimates obtained through ordinary least squares were scrutinized. To this purpose, I detected potentially influential observations with the largest studentized residuals through Bonferroni-adjusted outlier tests. Deleting these observations, however, did not make the treatment coefficient leave the confidence interval of the respective original regression.

Normality tests of the regression residuals did in most cases lead to a rejection of the normality hypothesis, even after transforming the dependent variables into a more normal-like shape by taking logarithms. Although, therefore, I cannot justify the assumption of normally distributed error terms substantively, regression coefficient estimates have been shown to be robust against this violation in sufficiently large sample sizes (Bohrstedt and Carter 1971, 123). The justification, then, relies on the central limit theorem which ensures an asymptotically normal sampling distribution, independent of the distribution in the population (Stock and Watson 2003, 43).

3.6.2.3 Comparability of experimental groups

Another potential threat to internal validity would be a lack of comparability of the treatment and the control group. Comparability requires identical composition, predispositions and experiences, and is warranted through randomization (Rossi, Freeman et al. 1999, 281).

For this experiment, randomization was realized by means of alternating experimental conditions for each newly incoming user. The alternation of conditions should produce the same results as a random numbers generator because users had no

influence on the order in which server requests were being processed. Likewise, they had no control over other participating users who were unknown and spread out over Germany and other countries. Consequently, alternation of experimental conditions can be assumed to be equivalent to randomization with random numbers.

Randomization minimizes the influence of confounding background factors. A relevant background factor in this experiment was the presentation of different final retailers in the product listings (see 3.4.3); another one was the accompanying advertisement for unrelated products on the same screen (see figure 5 and figure 6 the appendix I). Moreover, the exact visual stimulus delivery of website colors could not be controlled entirely, and may have differed among users due to variance in existing software, computers, and monitors (Birnbaum 2004, 811-812). Variance in available technology may have also had an impact on the speed of stimulus delivery (Reips 2002b, 245-246). Further confounding factors included a user's negative or positive experience with a particular appliance brand or a given online retailer, and all kinds of distractions that a user may have experienced at home or elsewhere while shopping online.

Although I examined the success of the random assignment with user characteristics such as browser and operating system, this inspection had its own limits. User characteristics were extracted from the user-agent string variable transmitted by the browser, and this variable could in principle be masked by the user (Tan and Kumar 2002, 16). Although it is impossible to estimate the amount of masking done, I assume that regular users for the most part have no incentive to mask their user-agent variable. Moreover, randomization should distribute masked variables evenly across experimental groups.

At first sight, Reips' concern that cookie technology would "exclude a large portion of participants" (Reips 2002b, 251) seems unwarranted given the high acceptance rate of persistent cookies of more than 95%. Yet, for technical reasons (see 3.2), I could not determine the number of users who rejected both persistent and temporary cookies. Therefore, it is impossible to present an overall non-acceptance rate.

Even a high acceptance of persistent cookies cannot ensure high experimental control because users may delete cookies themselves. That is, persistent cookies may be accepted by users at first, but deleted later on. Many internet browsers facilitate this behavior through an encompassing "clear private data" functionality that includes cookies. Unfortunately, those changes cannot be tracked at all. According to a representative survey for 2006, 80% of all German internet users are familiar with cookies; and 55% of all German internet users erase their cookies, either manually or automatically (Fisch and Gscheidle 2006, 438-439). The predecessor survey as of 2004 differentiated cookie erasure regarding its temporal occurrence. Accordingly, 37% of all German internet users erased their cookies directly after each session, and 42% of all users erased them at least once a week (van Eimeren, Gerhard et al. 2004, 368).

If a user returned to the experimental website without having any identifiable cookie, he would be randomly assigned again—independent of the group to which he had been assigned before. The probability of being assigned to an experimental group different from the prior one equaled 0.5. Subsequent returns with new random assignments would have further increased this probability.

Finally, even if all cookies were indeed persistent, I could not rule out the possibility that a given user accessed the experiment from different computers—for

example at work, and at home—and that these computers were assigned to different experimental conditions.

The above-described changes reduce the control over subjects' experimental assignment. If the treatment systematically changed users' propensity to delete their cookies, comparability and therefore internal validity would be threatened.

In sum, comparability is threatened through the use of different computers, of temporary cookies, and the erasure of persistent cookies. Unfortunately, the magnitude of this threat cannot be quantified.

3.6.2.4 Potential bias from switching experimental conditions

Regardless of the reason for a change in experimental condition, one has to ask what kind of bias could possibly result from it. Understanding this bias necessitates discriminating two basic cases. The first basic case may have occurred when a given user's assignment to the control group was followed by his assignment to the treatment group ("CT" case). The second basic case was just the opposite ("TC" case).

The CT case does not seem to be a major problem. Given that the shopbot was already in use and publicly accessible before the beginning of the actual experiment, every subject could potentially be CT. In this sense, prior exposure to the pre-experimental shopbot was like being in the control group later (while the experiment was being conducted). It is hard to see, however, why prior exposure to the regular website would have a problematic effect on the behavior of a subject that was subsequently assigned to the treatment group. Being more familiar with the website may make navigation easier, but it is unlikely to influence users' considerations of energy

efficiency. Therefore, CT is unlikely to induce bias with respect to energy efficiency.

TC, on the other hand, means that a subject saw life-cycle cost in the first assignment, and received regular product prices without life-cycle cost thereafter. This prior exposure to life-cycle cost estimates may have had a “priming” effect. Although several sorts of priming can be distinguished, they are all based on the same mechanism: if an individual is exposed to a given event, i.e. the prime, he will subsequently have easier access to information that already exists in his memory. The result of this increased accessibility, however, may differ. For example, it may not necessarily imply that the information under consideration is integrated into the individual’s decisions and actions (Mandel and Johnson 2002, 236).

Such priming is likely to make subjects concentrate more on energy cost than they would do otherwise, and make them buy appliances that are more efficient. This may have decreased the potential difference in energy efficiency between the treatment group and the control group and may have made it harder to reject the null hypothesis. The potential bias would thus be conservative in nature and would involve underestimating the effect of the life-cycle cost disclosure.

A similar way of putting the TC problem is to say that subjects may have become aware of the experiment. For example, as illustrated in section 3.4.2.4, users may have been able to discern the experimental structure (“powerprice_A” or “powerprice_B”) from the website addresses displayed. Still, given the field character of the experiment, online shoppers could be assumed to concentrate on the content of the website rather than on unsuspecting sounding website addresses. Moreover, chest freezers were not part of the experiment. Users in the treatment group who switched appliance categories between

upright freezers and chest freezers were shown life-cycle cost for the former, but only normal price information for the latter. A consumer who was treated first, but not treated thereafter may have wondered what was going on. If he concluded that he was part of an experiment about energy efficiency, he may have actively imitated the treatment, and he may have put an additional effort into calculating life-cycle cost by himself.

This problem can never be fully avoided in an online field experiment with open access because some treated consumers, i.e. those who have a particular interest in energy efficiency, may decide to actively inform other consumers about the existence of the life-cycle cost disclosure, even without knowing that it is part of an experiment. They may use personal web logs or tell institutions that deal with energy efficiency about the new feature of the website. Given that this feature was somewhat innovative, those institutions may spread the word in their own way. Such information dissemination was clearly out of my control and may have biased the results. Still, given the considerable cognitive effort and transaction cost associated with these kind of life-cycle cost calculations (if done by hand for a whole list of products), it is unlikely that subjects in the control group would have reached the same outcome as those in the treatment group.

Nevertheless, if other researchers interested in energy efficiency issues (see Reips 2002b, 253) became aware of the experimental character of the website, they may have scrutinized the website and may have lead to biased observations.

A bias that would inflate the treatment effect in the TC case is hard to imagine. Such an inflation would imply that users in the control group (who had been in the treatment group before) would click on *less* efficient appliances. A possible cause for this bias can be found in “resentful demoralization”, also known as the “screw you” effect

(Trochim 2004). Along this line of thought, untreated consumers could potentially have become angry and could have purposefully clicked on less efficient appliances than they would have done otherwise. This threat, however, appears to be largely theoretical given that consumers with limited budgets are unlikely to intentionally shop for appliances that cost them more over the long run. In other words, the fact that the experiment was conducted in a real purchasing situation seems to limit this threat.

Finally, the durability of cooling appliances limited the TC threat. Since these appliances represent long-term investments, it is unlikely that a given subject bought a cooling appliance first, and then returned to the website to buy another appliance of the same kind while the experiment was still running. This means that the TC threat described is likely to have virtually disappeared once a consumer had made a purchase decision.

Overall, the comparability of the treatment and control group is threatened by the use of cookies. The most likely bias, however, is conservative in nature and tends to reduce the treatment effect.

3.6.3 External validity

Generalizing the findings of this experiment to different contexts may face several limitations. In this section, I will discuss the potential influence of other times, places and persons (Trochim 2004).

First, the treatment effect may depend on time. Methodologically, the estimated effect represents an average value that refers to cross-sectional data gathered over the whole time span of the experiment. At any given point in time, the observed treatment

effect may have been smaller or larger, depending on interfering events that may have made consumers more aware of energy efficiency. An example for such interfering events may have been perceived changes in energy prices. Yet, the inclusion of the price of gas as a well-known indicator of energy price did not improve the fit of the regression models (see 3.6.1). Therefore, the treatment effect appears to have been relatively stable over time.

Second, there may have been something specific about the chosen shopbot that selectively attracted some consumers more than others. In addition, the shopbot itself had two different modes of which the search mode was not part of the experiment (see 3.2). Therefore, the experimental findings may be threatened by selection bias. This bias may involve a higher representation of online shoppers with an above- or below-average interest in issues of energy efficiency. If the experiment participants cared about energy efficiency more than average consumers do, those in the control group may have bought relatively more efficient appliances even without receiving life-cycle cost. This would imply a downward bias of the treatment effect. If, on the other hand, participating consumers cared less about energy efficiency than consumers do on average, the treatment effect would be biased upwards. The problem of selection bias may result from, e.g., the existing hyperlink structure and the kind of advertisement the shopbot runs. Consequently, differences between participating consumers and non-participating consumers may mask the intervention effect (Rossi, Freeman et al. 1999, 242). This bias cannot be estimated. Still, the large number of visitors on the website (see 3.2), and the long existence of the website suggest that this may be a minor problem.

Third, the range of cooling appliances in the shopbot database did not necessarily

include all appliances on the market. Yet, it contained several hundred models so that consumers could get a good overview of the range of purchasing options (see table 86 in appendix V, and table 96 in appendix VI).

In sum, the experimental findings primarily refer to the chosen website and its customers. While the results seem to be insensitive to changes in energy prices, they might look different for other websites and other consumers. The best way to deal with the challenge of further generalizability would be to repeat the experimental disclosure of life-cycle cost in various shopbots that differ with respect to website design and with respect to the customers they attract.

3.6.4 Measurement validity

The dependent and independent variables in this experiment refer to appliances for which users had clicked-through to final retailers. Measurement validity is threatened by double clicks, and by clicks from non-human user agents. Double clicks-throughs by the same user on exactly the same product sold by the same retailer were discarded (see 3.5.1).

Clicks from non-human user agents were treated at two levels. At a first level, these clicks had been filtered by Mentasys with the aid of special blacklists. At a second level, I scanned the user-agent string variable for conspicuous keywords (see 3.2), and I discarded observations from users with an unusually high total number of click-throughs (see 3.5.1).

The final check for potentially remaining clicks from non-human user agents consisted of using two sets of observations for regressions with energy use as the dependent variable. While the first set included all observations, the second was restricted

to each user’s final click-through. In this way, the influence from any remaining robot would have been greatly reduced to a single click-through per robot. Comparing the treatment effect on energy use between the two sets of observations shows that the results are very similar. Therefore, if any click-throughs from robots did indeed remain in the data set with all observations, they did not introduce a large bias. This robustness of the results implies high measurement validity.

3.6.5 Summary of threats to validity

When feasible and implemented correctly, randomized experiments represent the best approach to evaluating treatment effects (Rossi, Freeman et al. 1999; Trochim 2004, 305-306). Like many experiments, the one described here is not ideal, but suffers from several limitations that are summarized in the table below.

Table 38: Summary of threats to validity (shopbot)

<i>Cause</i>	<i>Potential bias</i>	<i>Effect on treatment outcome</i>	<i>Comment</i>
Use of cookies for randomization	Priming, imitation of treatment	–	Small given the relatively larger cognitive effort needed; Conservative bias
	Resentful demoralization of untreated	+	Unlikely given the real purchasing situation
Co-existence of experimental shopbot and regular search mode on the same shopbot website	Self-selection	?	Limits generalizability
Immeasurable characteristics of shopbot (advertising, hyperlink structure, reputation)	Self-selection	?	Limits generalizability

Chapter 4: Experimental online shop

4.1 Introduction

Overall, the online shop experiment was similarly structured as the shopbot experiment.

In this chapter, I describe the online shop data (4.2) and my hypothesis about the effect of life-cycle cost disclosure (4.3), followed by methods (4.4), results (4.5) and the related discussion (4.6). In addition to the quantitative evaluation of user behavior, I collected qualitative feedback from the treatment group and conducted supplementary in-depth interviews to better understand consumers' perception of life-cycle cost disclosure.

4.2 Data

The experimental data for washing machines 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 clothes, consumer electronics, and household appliances.

On the top of its home page, the online shop offers a range of pull-down menus from which users can choose products or product categories. After reaching the page with washing machines, users have two options how to proceed because on Quelle's website, two independent software systems for washing machines complement each other. One is run by Quelle itself. Here, the consumer navigates through menus to see different types and classes of washing machines. The other one, a more specialized recommendation agent, is embedded in the overall online shop and is independently operated by Mentasys. Therefore, only the latter was under experimental control and was used for gathering

data. 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 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. Expert search allows for more detailed entering of preferences, and provides a more structured output of key appliance attributes.

Technically, data collection and preparation was done in the same way as for the shopbot (see section 3.2). As to the two recommendation modes, pre-treatment preferences elicited in the Expert search mode were not logged by the server. Therefore, fewer covariates were available for regressions with Expert search data. Moreover, due to proprietary information concerns, data that would facilitate estimating the number of online purchases per day cannot be disclosed here.

Additional data regarding gasoline prices for the time period of the experiment was obtained from the Association of the German Petroleum Industry (MWV 2006).

The supplementary qualitative data about users' perception of life-cycle cost disclosure was gathered in two different ways. First, the recommendation agent allowed customers to send back anonymous feedback about their shopping experience; and feedback from the treatment group was evaluated for this dissertation. Alternatively, customers could choose to leave their email address for further communication with the online shop. Among those who left their email address, eight customers were willing to

participate in in-depth interviews about their perception of life-cycle cost disclosure.

4.3 Hypotheses

With the data from Quelle, I propose to test several hypotheses. A more detailed reasoning for my choice of two-tailed tests is provided in section 3.3.

H_{1a}: “The disclosure of life-cycle cost does not make online shoppers opt for household appliances that are different in terms of their energy efficiency.”

H_{1b}: “The disclosure of life-cycle cost makes online shoppers opt for household appliances that are different in terms of their energy efficiency.”

Analogously, a similar null hypothesis (H_{2a}) will be tested regarding the potential change in water efficiency of the chosen appliances.

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

H_{3a}: “The disclosure of life-cycle cost does not make online shoppers opt for household appliances that are different in terms of their estimated life-cycle cost.”

H_{3b}: “The disclosure of life-cycle cost makes online shoppers opt for household appliances that are different in terms of their estimated life-cycle cost.”

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

H_{4a}: “The disclosure of life-cycle cost does not change the number of products put into the virtual shopping cart.”

H_{4b}: “The disclosure of life-cycle cost changes the number of products put into the virtual shopping cart.”

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

H_{5a}: “The disclosure of life-cycle cost does not change the price of products put into the virtual shopping cart.”

H_{5b}: “The disclosure of life-cycle cost changes the price of products put into the virtual shopping cart.”

4.4 Method

This section includes a description of the treatment (4.4.1), the procedure (4.4.2), the chosen measures (4.4.3), the regression models (4.4.4) and the qualitative analysis of customer feedback (4.4.5).




4.4.1 Treatment

In many respects, the treatment in the online shop was similar to the treatment in the shopbot described in section 3.4.2. Therefore, I only describe those features in detail that differ from the shopbot design. This includes the display and calculation of cost (4.4.1.1), the display of usage assumptions and their adjustment (4.4.1.2), the default assumptions for prices and preferences (4.4.1.3), and the technical implementation of the experiment (4.4.1.4).

4.4.1.1 Display and calculation of cost

While the two recommendation modes available—Simple search and Expert search—had their own treatment and control groups, the basic difference between each respective experimental condition regarding life-cycle cost disclosure, however, was the same. Table 39 shows the experimental conditions in the Simple search mode. All details concerning visual stimuli are shown in appendix II.

Table 39: Conditions in the Simple search mode of the online shop

<i>Experimental condition and default assumptions</i>	<i>Visual stimuli for sample washing machine</i>	
Control	 <p>Bild vergrößern</p> <p><input type="checkbox"/> Vergleich</p>	<p>Miele W 4146 WPS Leistungsstark und zuverlässig.</p> <p>Auf einen Blick Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.</p> <p>1.159,95 €</p> <p>Produktdetails anzeigen → in den Warenkorb legen!</p> <p>Wie gut passt dieses Produkt zu Ihren Anforderungen? →</p>
<p>Treatment round 1</p> <ul style="list-style-type: none"> • <i>Time horizon:</i> 4.9 years • <i>Price of electricity:</i> 0.16 € / kWh • <i>Price of water:</i> 3.95 € / m³ • <i>Standard cycles per week:</i> 3 	 <p>Bild vergrößern</p> <p><input type="checkbox"/> Vergleich</p>	<p>Miele W 4146 WPS Leistungsstark und zuverlässig.</p> <p>Auf einen Blick Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.</p> <p>Gesamtkosten = Preis + Betriebskosten 1.426,61 € = 1.159,95 € + 266,66 €</p> <p>Produktdetails anzeigen → in den Warenkorb legen!</p> <p>Wie gut passt dieses Produkt zu Ihren Anforderungen? →</p>
<p>Treatment round 2</p> <ul style="list-style-type: none"> • <i>Time horizon:</i> 9 years • <i>Price of electricity:</i> 0.16 € / kWh • <i>Price of water:</i> 3.95 € / m³ • <i>Standard cycles per week:</i> 3 	 <p>Bild vergrößern</p> <p><input type="checkbox"/> Vergleich</p>	<p>Miele W 4146 WPS Leistungsstark und zuverlässig.</p> <p>Auf einen Blick Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.</p> <p>1.159,95 €</p> <p>Betriebskosten ⓘ (bei 9,0 Jahren Nutzung) Gesamtkosten = Preis + <u>geschätzte Betriebskosten</u> 1.649,74 € = 1.159,95 € + 489,79 €</p> <p>Produktdetails anzeigen → in den Warenkorb legen!</p> <p>Wie gut passt dieses Produkt zu Ihren Anforderungen? →</p>

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, and cost information, where applicable. Operating cost can be adjusted by clicking on “Betriebskosten”. Via the links in the second last line, one can receive more detailed product information, or put the appliance into the virtual shopping cart, respectively. In the last line, the user can tick the box for an in-depth comparison of appliance alternatives, and receive detailed feedback for each product as to how it performs relative to the user’s preferences.

As in the shopbot case, life-cycle costs (LCC) are estimated based on the following general formula:

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

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 are calculated as

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

where P_E = price of electricity [€/kWh], C_E = consumption of energy [kWh/cycle], P_W = price of water [€/m³], C_W = consumption of water [m³/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 what most of the energy efficiency

websites reviewed in chapter 2 present.

4.4.1.2 Display of usage assumptions and their adjustment

The treatment group was able to actively adjust the usage assumptions that underlie the life-cycle cost estimation. For calculating the present value of future operating cost, I considered two alternative forms of discounting. After pre-testing *direct* discounting, I eventually settled for *indirect* discounting as demonstrated in section 3.4.2.2. Figure 3 illustrates how users were able to adjust the assumptions in the online shop.

Figure 3: Adjustment of assumptions in the treatment group of the online shop

QUELLE-Berater / »Waschmaschinen suchen ein Zuhause«

Betriebskostenschätzung

Die Schätzung der Betriebskosten basiert auf den unten stehenden Annahmen. Diese Durchschnittswerte können Sie individuell anpassen. Mögliche zukünftige Änderungen der Strom- und Wasserpreise werden nicht berücksichtigt.

Nutzungen pro Woche:	<input type="text" value="3,0"/>	Anzahl	Nutzungsdauer:	<input type="text" value="9,0"/>	Jahre
Wasserpreis:	<input type="text" value="3,95"/>	€/m³	Strompreis:	<input type="text" value="0,16"/>	€/kWh

Die Betriebskosten werden folgendermaßen abgeschätzt:

Betriebskosten = (Strompreis x Strom-Verbrauch + Wasserpreis x Wasser-Verbrauch) x Nutzungshäufigkeit x Nutzungsdauer

z.B.: 526,89 € = (0,16 €/kWh x 1 kWh + 3,95 €/m³ x 0,045 m³) x 3 x 52 /Jahr x 10 Jahre

Dieses Beispiel dient nur der Veranschaulichung und bezieht sich nicht auf die angezeigten Geräte.

The first paragraph explains that the estimation relies on adjustable assumptions (shown in the second paragraph), and that the default assumptions represent average values. It also cautions that the estimation is static in nature and that it does not reflect potential future changes in electricity and water prices. The three paragraphs at the

bottom illustrate the estimation formula with a sample calculation and make explicitly clear that the sample calculation not refer to any appliance currently looked at by the consumer.

4.4.1.3 Default assumptions for estimating operating cost

Given the application of indirect discounting, the resulting overall equation for life-cycle cost (LCC) 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 = consumption of energy [kWh/cycle], P_W = price of water [€/m³], C_W = consumption of water [m³/cycle], m = number of cycles per week [cycles/week], and $k = 52$ [weeks/year].

Table 40 exhibits the default assumptions for the estimation of operating cost for washing machines.

Table 40: Default assumptions for estimating washing machines' operating costs

<i>Default assumption</i>	<i>Default value</i>	<i>Unit</i>	<i>Reference year</i>	<i>Comment (Reference)</i>
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 (GfK 2006)
Frequency of use	3	cycles/week	2002	Rounded to integer (derived from 12.2 times per month) (Schlomann, Gruber et al. 2004, 72)
Equivalent time horizon (treatment round 1)	4.9	years	2004	Based on implicit discount rate of 18% derived from (Kuckartz and Rheingans-Heintze 2004, 81)
Equivalent time horizon (treatment round 2)	9	years	2006	Based on implicit discount rate of about 6%; closer to then current long-term interest rate of about 4% (Deutsche Bundesbank 2006)

4.4.1.4 Technical implementation of the experiment

The technical implementation in the online shop differed from the shopbot case (3.4.2.4) regarding the revelation of the experimental structure, the checking of randomization and the use of JavaScript.

The experimental structure was impossible to discern from the internet addresses visible to users , as shown in table 41.

Table 41: Sample Uniform Resource Locators for the online shop

<i>Experimental condition</i>	<i>URL</i>
Control group	http://www.quelle.de/is-bin/INTERSHOP.enfinity/eCS/Store/de/-/EUR/Q_ViewStatic-ViewSalesAssistant;sid=qYKuvexaiqyun6gkeE4CqY8SE-_BikMedRQ=?CategoryName=50000306&SalesAssistant=wama_b&Linktype=J
Treatment group	http://www.quelle.de/is-bin/INTERSHOP.enfinity/eCS/Store/de/-/EUR/Q_ViewStatic-ViewSalesAssistant;sid=9Tr2cvE0hIv2WbVKJGVaZpJ8T1eZRd_ZedI=?CategoryName=50000306&SalesAssistant=wama_b&Linktype=J

For the purpose of checking the success of random assignment, more user characteristics were available. Not only could I regress the treatment dummy on user characteristics distilled from the user-agent variable such as browser and operating system used; I also regressed the treatment variable on pre-treatment preferences elicited in the Simple search recommendation mode.

Moreover, JavaScript needed to be activated on users' computers. JavaScript was required for seeing all pull-down menus of the online shop in general, and for starting the recommendation agent in particular.

4.4.2 Procedure

In order to assure realistic conditions for this field experiment, data was collected without obtaining participants' informed consent prior to participation. This procedure had been approved by the University of Maryland's Institutional Review Board (Application No. 01591). The interviews were conducted over the telephone after obtaining the participants' informed consent.

The figures referred to in this section can all be found in appendix II unless otherwise noted. Figure 12 illustrates the experimental process at the online shop. Consumers arrived at the homepage of the online shop (figure 13) and started the recommendation agent which offered them a choice between two alternative recommendation modes—Simple search and Expert search (figure 14). In the Simple search mode, the subsequent preference elicitation consisted of five different questions (figure 15), while in the Expert search mode, users could specify up to 12 preferences (figure 16 and table 79). 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. Operating and life-cycle cost for the treatment group were estimated based on default usage assumptions as listed in table 40. Treatment round one had a default time horizon of 4.9 years, and treatment round two a time horizon of nine years.

The display of products differed between the two recommendation modes. Simple search presented one main recommendation, and two alternative products on the first page, and users could see more alternatives only by moving on to subsequent pages. Figure 17 exhibits a Simple search recommendation for the control group, whereas figure 18 shows the same recommendation for the treatment group. Expert search, on the other hand, presented a much longer list of products without differentiating explicitly between a main “recommendation” on top, and less prominent “alternatives” below. Figure 19 depicts the Expert search mode for the treatment group.

Regardless of the chosen recommendation mode, users in the treatment group could adjust the underlying assumptions for the calculation of operating costs (see figure 3 in 4.4.1.2) In addition, in round two of the experiment, they could also choose to receive additional information about the significance of operating cost (figure 20)

Furthermore, both experimental groups could choose to see an in-depth comparison in matrix format with detailed product characteristics. The matrix for the treatment group consisted of two additional lines showing operating and life-cycle cost, respectively (figure 21).

Finally, the recommendation agent allowed users to receive detailed feedback for each product as to how it performed relative to the user's preferences (figure 22).

4.4.3 Measures

Most of the dependent and independent variables used in this experiment refer to products that users had put into the virtual shopping cart by clicking on a specific link.

The dependent variables of primary interest were energy and water consumption per standard washing cycle. Further dependent variables were purchase price, operating cost, and life-cycle cost. Since 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 default assumptions about price and time horizon. All dependent variables of interest are shown in table 42.

Table 42: Key dependent variables in the online shop experiment

<i>Dependent variable</i>	<i>Meaning / Comment</i>
energy	Energy use of appliance [kWh/standard cycle]
water	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 used are shown in Table 43.

Table 43: Key independent variables in the online shop experiment

<i>Independent variables</i>	<i>Meaning / Comment</i>
treatment	Treatment dummy variable
mode	Recommendation mode (Simple search/Expert search)
price	Price of appliance [€]
capacity	Total capacity of the appliance [L]
efficiency class	Energy efficiency class (A - F) dummy variables
brands	Appliance brand dummy variables
programs	Dummy variables for short wash cycle and other programs
price difference	Difference between regular and special price [€]
preferences	User preference (size, type, price) dummy variables
cookie	Cookie type (persistent/session cookie)
firefox, msie, opera, mac	Browser dummy variables (extracted from user-agent)

4.4.4 Models

I used the following regression model for testing hypothesis H_{1a}—that the energy-efficiency of chosen products is unaffected by the treatment:

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

where *energy* = energy use [kWh/cycle] for cooling appliance *i*, *treatment* = treatment dummy variable, *Z* = vector of covariates (see below), and *u* = error term. This basic model was estimated separately for each recommendation mode. In addition, I also employed a logarithmic specification:

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

This form of the model implied that life-cycle cost disclosure would lead to a constant percentage change in energy use. Similar models were estimated for water use, estimated life-cycle cost, and appliance prices as dependent variables. I estimated all models with ordinary least squares.

As a special case, the vector of covariates *Z* included interactions between appliance capacity and the treatment dummy.

For investigating the hypothesis H_{3a} that the treatment does not change online shoppers' number of click-throughs to final retailers, I relied on chi-square tests of statistical independence and 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. The range of potential covariates is greatly reduced here because *CTCOUNT* refers to a sum of click-throughs. While each click-through refers to individual product characteristics, the *sum* of click-throughs can only be associated with characteristics that are stable over time and that do not change with each click, such as browsers.

4.4.5 Supplementary analysis of user feedback

This section describes the online form used for obtaining customer feedback on the recommendation agent (4.4.5.1), and the in-depth telephone interviews conducted with a subgroup of those customers who actually returned the feedback form (4.4.5.2).

4.4.5.1 Feedback form

The feedback form consisted of questions (1) regarding overall customer satisfaction with the performance of the recommendation system, (2) regarding the importance of individual features, (3) whether the customer could find a suitable washing machine, (4) whether the customer had already visited another consumer website that offers operating cost information, (5) whether the customer had any other suggestions, and (6) whether the customer was interested in having recommendation agents available for products other than washing machines. Figure 23 in appendix III exhibits the feedback form.

For questions 1, 3, and 4, users could choose their respective answers from pull-down menus (table 80 in appendix III). Questions 2 and 5 allowed users to tick one or more boxes for providing one or more answers, respectively. Finally, users could leave their email address for follow-up contact.

Note that in both the feedback form and the telephone interviews, the term “life-cycle cost” was avoided. Instead, I only referred to “operating cost” for better comprehension. Nevertheless, I implicitly referred to life-cycle cost because those were also provided to the treatment group.

4.4.5.2 Telephone interview

Participants were recruited through the online shop's feedback form. Those that left an email address were asked by email whether they would be available for a follow-up interview. If they answered in the affirmative, I called them at home, asked for their informed consent to be interviewed, and offered them a 10 Euro gift certificate for participation. All interviews were completed without any dropout, and participants received their gift certificates. I recorded all interviews on minidisk, transcribed them, and erased the minidisks thereafter.

Patton (1990) distinguishes three forms of qualitative, open-ended interviews: the informal conversational interview, the general interview guide approach, and the standardized open-ended interview (Patton 1990, 280). The interviews conducted for this dissertation followed the general interview guide approach in that I had a “general plan of inquiry” (Babbie 2004, 300) rather than a list of standardized questions. This procedure kept the interview flexible enough and provided an opportunity for participants to address topics of their own choice.

The following issues were addressed in the interviews: (1) The participant's reaction to, and understanding of the disclosed operating cost, (2) assumptions that underlie the calculated operating cost, their potential adjustment, and the role of rising energy prices, (3) the importance of energy efficiency for the participant, (4) his/her knowledge of alternative information channels regarding energy efficiency of appliances, (5) his/her personal opinion about the future of operating cost disclosure, and (6) his/her further comments, if any.

4.5 Results

Results from the online shop experiment are differentiated by treatment rounds and recommendation modes. Section 4.5.1 contains results from the first treatment round with an underlying time horizon of 4.9 years, and section 4.5.2 those from the second treatment round with a time horizon of nine years. All results are discussed in section 4.6.

4.5.1 First treatment round

While stimulus delivery worked as planned, randomization, cookie acceptance and problematic clicking behavior needed to be considered in detail.

The days during which the stimulus was delivered and click-through data was gathered are documented in figure 46 in appendix VII.

Randomization worked well for all users visiting the experimental website. The distribution of those users who actually clicked-through to final retailers, however, was not as equalized (see table 103 in appendix VII).

Persistent cookies were accepted by more than 92% of all users in treatment round one. Rejection of persistent cookies occurred exclusively in the Expert search mode (see table 104 in appendix VII).

Problematic clicks due to repeated clicking on the same product or due to a high total number of click-throughs amounted to 2927 observations and were discarded. The cut-off point for an usually high total number of click-throughs was 20 (see table 106 in appendix VII).

Overall, about 46000 separately identifiable users visited the online shop during round one of the experiment. In both recommendation modes, they were shown about

150 washing machines from 7 different brands (see table 105 in appendix VII.)

Appendix VII provides more detailed information on the range of life-cycle cost (figure 47), energy use box plots (figure 48), energy use histograms (figure 49), energy efficiency classes (figure 50), water use (figure 51) life-cycle cost histograms (figure 52), and energy versus capacity scatter plots (figure 53).

4.5.1.1 Simple search

In the Simple search recommendation mode, both mean and median energy use are lower in the treatment group than in the control group (table 44). The same is true for mean water use, while median water use is the same in both groups (table 45). Mean life-cycle cost is relatively higher in the treatment group; median life-cycle cost is the same (table 46).

Table 44: Descriptive statistics for energy use (Ssearch online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	624	0.943	0.95	0.103	0.83	1.36
Treatment	611	0.942	0.85	0.106	0.68	1.36
Total	1235	0.943	0.89	0.105	0.68	1.36

Note: Energy in [kWh/cycle].

Table 45: Descriptive statistics for water use (Ssearch online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean water</i>	<i>Median water</i>	<i>SD water</i>	<i>Min. water</i>	<i>Max. water</i>
Control	624	44.71	42	4.4	35	60
Treatment	611	44.69	42	4.4	34	60
Total	1235	44.70	42	4.4	34	60

Note: Water in [L/cycle].

Table 46: Descriptive statistics for life-cycle cost (Ssearch online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	624	716	681	94	605	1312
Treatment	611	723	681	122	407	1741
Total	1235	719	681	109	407	1741

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 47 below shows regression results for energy use, water use, and life-cycle costs. When controlling for other factors, the treatment reduces energy use by 1.2% in model (4). This effect is significant at a 5% level.

Table 47: Effect on energy use, water and cost (Ssearch online shop round 1)

	<i>ln(energy)</i>			<i>ln(water)</i>	<i>ln(lccost)</i>	
	(1) All CT	(2) All CT	(3) Final CT	(4) Final CT	(5) All CT	(6) All CT
treatment	-0.0015 (0.0061)	-0.0055 (0.0037)	-0.0078 (0.0053)	-0.012* (0.0046)	-0.0062 (0.0038)	0.0037 (0.0057)
ln(capacity)		0.75*** (0.024)	0.68*** (0.027)	0.76*** (0.026)	0.59*** (0.025)	0.31*** (0.037)
constant	-0.064*** (0.0042)	-1.14*** (0.11)	-1.26*** (0.16)	-1.11*** (0.13)	3.12*** (0.088)	6.31*** (0.16)
efficiency class	No	Yes	No	Yes	Yes	Yes
brands	No	Yes	No	Yes	Yes	Yes
other features	No	Yes	Yes	Yes	Yes	Yes
preferences	No	Yes	Yes	Yes	Yes	Yes
adj. R-sq	-0.001	0.652	0.571	0.678	0.550	0.480
N	1235	1235	780	780	1235	1235

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. Models 3 to 4 contain only final CTs and serve as a robustness check for models 1 to 2. See figure 54 in appendix VII for residual histograms.

4.5.1.2 Expert search

While median energy use is the same, mean energy use is higher in the treatment group

than in the control group (table 48). Mean water use is lower in the treatment group; median water use is the same (table 49). Regarding life-cycle cost, the treatment group has a higher mean, but does not differ from the control group with respect to the median (table 50).

Table 48: Descriptive statistics for energy use (Esearch online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	617	0.917	0.85	0.107	0.57	1.19
Treatment	534	0.920	0.85	0.103	0.57	1.36
Total	1151	0.918	0.85	0.105	0.57	1.36

Note: Energy in [kWh/cycle].

Table 49: Descriptive statistics for water use (Esearch online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean water</i>	<i>Median water</i>	<i>SD water</i>	<i>Min. water</i>	<i>Max. water</i>
Control	617	43.15	42	4.7	35	56
Treatment	534	42.60	42	4.3	35	60
Total	1151	42.89	42	4.5	35	60

Note: Water in [L/cycle].

Table 50: Descriptive statistics for life-cycle cost (Esearch online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	617	726	716	101	605	1312
Treatment	534	755	716	159	477	2447
Total	1151	739	716	132	477	2447

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 51 exhibits regression results for energy, water use and life-cycle cost. Water use is reduced through the treatment by 1.1% on average ($p < 0.05$), holding other factors constant. Conversely, life-cycle costs get increased through the treatment by 2.7% ($p < 0.01$).

Table 51: Effect on energy use, water and cost (Esearch online shop round 1)

	<i>ln(energy)</i>			<i>ln(water)</i>	<i>ln(lccost)</i>	
	(1) All CT	(2) All CT	(3) Final CT	(4) Final CT	(5) All CT	(6) All CT
treatment	0.0037 (0.0067)	0.0049 (0.0048)	0.0049 (0.0044)	0.0037 (0.0051)	-0.011* (0.0048)	0.027** (0.0085)
ln(capacity)		0.64*** (0.025)	0.67*** (0.024)	0.75*** (0.020)	0.41*** (0.030)	0.17*** (0.032)
constant	-0.094*** (0.0047)	-1.18*** (0.041)	-1.34*** (0.029)	-1.25*** (0.052)	3.47*** (0.094)	6.62*** (0.060)
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	-0.001	0.499	0.591	0.688	0.391	0.180
N	1151	1151	1151	704	1151	1151

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. Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3. See figure 54 in appendix VII for residual histograms.

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

This section refers to the combined observations from both recommendation modes. The two experimental groups do not differ in terms of their median energy use, but mean energy use is higher in the treatment group (table 52). The median is also the same for water use, but mean water use is lower in the treatment group (table 53). As to life-cycle cost, both mean and median are higher in the treatment group (table 54).

Table 52: Descriptive statistics for overall energy use (online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	1241	0.930	0.85	0.105	0.57	1.36
Treatment	1145	0.932	0.85	0.105	0.57	1.36
Total	2386	0.931	0.85	0.105	0.57	1.36

Note: Energy in [kWh/cycle].

Table 53: Descriptive statistics for overall water use (online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean water</i>	<i>Median water</i>	<i>SD water</i>	<i>Min. water</i>	<i>Max. water</i>
Control	1241	43.93	42	4.6	35	60
Treatment	1145	43.71	42	4.5	34	60
Total	2386	43.83	42	4.5	34	60

Note: Water in [L/cycle].

Table 54: Descriptive statistics for overall life-cycle cost (online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	1241	721	703	98	605	1312
Treatment	1145	738	714	141	407	2447
Total	2386	729	703	121	407	2447

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.

When controlling for other factors (table 55), the treatment coefficients for water use and life-cycle cost are significant at a 5% level. Accordingly, being in the treatment group is associated with a decrease in water use by 0.72% and with an increase in life-cycle cost by 1.4%.

Table 55: Effect on overall energy use, water and cost (online shop round 1)

	<i>ln(energy)</i>			(4) Final CT	<i>ln(water)</i>	<i>ln(lccost)</i>
	(1) All CT	(2) All CT	(3) All CT		(5) All CT	(6) All CT
treatment	0.0018 (0.0046)	0.00025 (0.0035)	0.00029 (0.0032)	-0.00054 (0.0039)	-0.0072* (0.0033)	0.014** (0.0053)
ln(capacity)		0.57*** (0.020)	0.66*** (0.017)	0.72*** (0.020)	0.47*** (0.021)	0.34*** (0.031)
mode			-0.0038 (0.0033)	-0.0034 (0.0040)	-0.021*** (0.0033)	0.031*** (0.0053)
constant	-0.079*** (0.0032)	-1.15*** (0.029)	-1.27*** (0.017)	-1.23*** (0.047)	3.36*** (0.068)	5.74*** (0.13)
efficiency class	No	No	Yes	Yes	Yes	Yes
brands	No	No	Yes	Yes	Yes	Yes
other features	No	Yes	Yes	Yes	Yes	Yes
adj. R-sq	-0.000	0.419	0.515	0.574	0.403	0.256
N	2386	2386	2386	1484	2386	2386

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. See figure 54 in appendix VII for residual histograms.

The effect sizes (f^2) of all regressions reported above range from 0.0021 to 0.0092
 (see table 109 in appendix VII).

4.5.1.4 Overall impact on retail volume

From a business perspective, the turnover generated by the recommendation agent is important—which depends on both appliance prices and click-throughs. Table 56 shows that the sum of prices is higher in the control group, while the mean price is higher in the treatment group. The mean number of click-throughs is lower in the treatment group (table 57).

Table 56: Descriptive statistics for appliance prices (online shop round 1)

<i>All click-throughs</i>	<i>N</i>	<i>Sum price</i>	<i>Mean price</i>	<i>SD price</i>	<i>Min. price</i>	<i>Max. price</i>
Control	1241	588884	475	99	350	1039
Treatment	1145	550522	481	106	300	1039
Total	2386	1139406	478	103	300	1039

Note: Prices in [Euros]

Table 57: Descriptive statistics for number of clicks per user (online shop round 1)

<i>All click-throughs</i>	<i>N users</i>	<i>Mean CT count</i>	<i>Median CT count</i>	<i>SD CT count</i>	<i>Min. CT count</i>	<i>Max. CT count</i>
Control	23195	0.054	0	0.38	0	19
Treatment	23073	0.050	0	0.37	0	18
Total	46268	0.052	0	0.37	0	19

Note: CT: click-throughs

A chi-square test of independence shows that prices are not differently distributed across the two experimental groups at a 5% level, but $p=0.057$ (see table 114 in appendix VII). Another chi-square test for the number of click-throughs makes it much harder to reject the hypothesis of independence ($p=0.36$ —see table 113 in appendix VII).

Table 58 below presents regression results for appliance prices. The treatment leads to a decrease in appliance prices for small capacities, and to an increase in prices for large capacities. In model (1), the treatment effect is negative for capacities smaller than 6 liters, and positive otherwise. In model (3), the treatment effect is negative for capacities smaller than 5 liters, and positive otherwise. At the median capacity (5 L), the treatment effect increases price by 0.31% (see table 108 in appendix VII for capacity quartiles).

The number of click-throughs is not significantly affected by the experimental conditions at a 5% level when controlling for other factors (see table 59 below), but the model has a relatively poor goodness of fit.

Table 58: Effect on appliance prices (online shop round 1)

	(1) Simple search	<i>ln(price)</i> (2) Expert search	(3) Overall
treatment	-0.35** (0.11)	-0.26 (0.14)	-0.19* (0.084)
treat.*ln(cap.)	0.20** (0.063)	0.17* (0.084)	0.12* (0.049)
ln(capacity)	0.10 (0.055)	-0.098* (0.046)	0.085* (0.037)
mode			0.037*** (0.0061)
constant	7.21*** (0.18)	6.88*** (0.079)	7.20*** (0.067)
efficiency class	Yes	Yes	Yes
brands	Yes	Yes	Yes
other features	Yes	Yes	Yes
preferences	Yes	No	No
adj. R-sq	0.516	0.181	0.425
N	1235	1151	2386

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, mode: recommendation mode (Simple search, Expert search).

Table 59: Effect on the overall number of click-throughs (online shop round 1)

	<i>Count of click-throughs per user</i>
treatment	-0.072 (0.061)
mode	0.77*** (0.062)
constant	-7.71*** (0.28)
lnalpha constant	2.04*** (0.050)
browsers	Yes
pseudo R-sq	0.199
N	46268

Note: Standard errors of the negative binomial regressions in parentheses. * p<0.05, ** p<0.01, *** p<0.001, mode: recommendation mode

4.5.2 Second treatment round

Figure 55 (in appendix VIII) shows the click-throughs from the second treatment round over time. Potential problems might have been due to randomization, cookie acceptance, and the handling of problematic clicking behavior.

Randomization worked well for all users. Different from the other results described in this dissertation, it also worked well for click-throughs (see table 115 in appendix VIII).

Persistent cookies were accepted by more than 90% of all users with all rejections of persistent cookies occurring in the Expert search mode (see table 116 in appendix VIII).

Problematic clicks due to repeated clicking on the same product or due to a high total number of click-throughs amounted to 2123 observations and were discarded. The cut-off point for an usually high total number of click-throughs was the same as in round one (20 clicks—see table 118 in appendix VIII).

Overall, about 95000 separately identifiable users visited the shopbot. In each respective appliance category, they were shown more than 160 different appliances from 7 brands (see table 117 in appendix VIII).

Appendix VIII provides more detailed information on the range of life-cycle cost (figure 56), energy use box plots (figure 57), energy use histograms (figure 58), energy efficiency class histograms (figure 59), water use histograms (figure 60), life-cycle cost histograms (figure 61) and energy versus capacity scatterplots (figure 62).

4.5.2.1 Simple search

Median energy use, water use, and life-cycle cost are the same in both experimental groups. Mean energy use is lower in the treatment group (table 60), and the same holds for mean water use (table 61). Differently, mean life-cycle cost is higher in the treatment group (table 62).

Table 60: Descriptive statistics for energy use (Ssearch online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	498	0.999	1.02	0.111	0.57	1.36
Treatment	492	0.990	1.02	0.112	0.57	1.36
Total	990	0.994	1.02	0.112	0.57	1.36

Note: Energy in [kWh/cycle].

Table 61: Descriptive statistics for water use (Ssearch online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean water</i>	<i>Median water</i>	<i>SD water</i>	<i>Min. water</i>	<i>Max. water</i>
Control	498	45.80	48	4.7	34	60
Treatment	492	45.38	48	4.8	34	60
Total	990	45.59	48	4.8	34	60

Note: Water in [L/cycle].

Table 62: Descriptive statistics for life-cycle cost (Ssearch online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	498	950	901	134	798	1650
Treatment	492	959	901	159	682	1780
Total	990	955	901	147	682	1780

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.

When controlling for other factors, the treatment has a negative effect on energy use that is statistically significant at a 5% level (table 63). Being in the treatment group reduces average energy use by 0.69% (model 3), and 0.81% (model 4), respectively.

Table 63: Effect on energy use, water and cost (Ssearch online shop round 2)

	<i>ln(energy)</i>			<i>ln(water)</i>	<i>ln(lccost)</i>	
	(1) All CT	(2) All CT	(3) All CT	(4) Final CT	(5) All CT	(6) All CT
treatment	-0.0091 (0.0072)	-0.0058 (0.0036)	-0.0069* (0.0030)	-0.0081* (0.0037)	-0.0036 (0.0042)	-0.0011 (0.0050)
ln(capacity)		0.80*** (0.015)	0.91*** (0.015)	0.92*** (0.020)	0.76*** (0.027)	0.41*** (0.041)
constant	-0.0073 (0.0050)	-1.38*** (0.027)	-1.73*** (0.027)	-1.38*** (0.027)	2.73*** (0.051)	6.43*** (0.091)
efficiency class	No	No	Yes	Yes	Yes	Yes
brands	No	No	Yes	Yes	Yes	Yes
other features	No	No	Yes	Yes	Yes	Yes
preferences	No	No	Yes	Yes	Yes	Yes
adj. R-sq	0.001	0.752	0.845	0.834	0.622	0.683
N	990	990	990	712	990	990

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. eeclclass: energy efficiency class.
 Model 4 contains only final CTs and serves as a robustness check for models 1 to 3.
 See figure 63 in appendix VIII for residual histograms.

4.5.2.2 Expert search

Both mean and median energy use are lower in the treatment group than in the control group (table 64). The same is true for mean water use, while median water use is the same (table 65). Similarly, mean life-cycle cost is lower in the treatment group, and median life-cycle cost is the same (table 66).

Table 64: Descriptive statistics for energy use (Esearch online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
Control	542	0.954	0.95	0.119	0.57	1.36
Treatment	533	0.936	0.89	0.111	0.57	1.19
Total	1075	0.945	0.94	0.115	0.57	1.36

Note: Energy in [kWh/cycle].

Table 65: Descriptive statistics for water use (Esearch online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean water</i>	<i>Median water</i>	<i>SD water</i>	<i>Min. water</i>	<i>Max. water</i>
Control	542	42.92	42	4.9	35	60
Treatment	533	42.36	42	4.5	35	56
Total	1075	42.65	42	4.7	35	60

Note: Water in [L/cycle].

Table 66: Descriptive statistics for life-cycle cost (Esearch online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
Control	542	956	901	135	798	1650
Treatment	533	947	901	144	549	2043
Total	1075	951	901	139	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 67 below presents regression results for energy use, water use and life-cycle cost. The treatment on average reduces energy use by 0.92% (model 2) to 1% (model 3). It also reduces water use by 0.97% (model 5). These effects are significant at a 5% level.

Table 67: Effect on energy use, water and cost (Esearch online shop round 2)

	<i>ln(energy)</i>			<i>ln(water)</i>	<i>ln(lccost)</i>	
	(1) All CT	(2) All CT	(3) All CT	(4) Final CT	(5) All CT	(6) All CT
treatment	-0.018* (0.0075)	-0.0092* (0.0037)	-0.010*** (0.0031)	-0.0096* (0.0038)	-0.0097* (0.0046)	-0.00059 (0.0062)
ln(capacity)		0.91*** (0.017)	1.00*** (0.015)	1.00*** (0.017)	0.84*** (0.029)	0.34*** (0.035)
constant	-0.055*** (0.0055)	-1.58*** (0.018)	-1.75*** (0.018)	-1.74*** (0.022)	2.75*** (0.032)	6.43*** (0.059)
efficiency class	No	No	Yes	Yes	Yes	Yes
brands	No	No	Yes	Yes	No	Yes
other features	No	Yes	Yes	Yes	Yes	Yes
adj. R-sq	0.004	0.758	0.833	0.849	0.537	0.408
N	1075	1075	1075	725	1075	1075

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. eeclass: energy efficiency class.
 Models 4 to 5 contain only final CTs and serve as a robustness check for models 1 to 3.
 See figure 63 in appendix VIII for residual histograms.

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

When combining the observations from both recommendation modes, both mean and median energy use are lower in the treatment group (table 68). The same is true for water use (table 69). 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 70).

Table 68: Descriptive statistics for overall energy use (online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean energy</i>	<i>Median energy</i>	<i>SD energy</i>	<i>Min. energy</i>	<i>Max. energy</i>
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 69: Descriptive statistics for overall water use (online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean water</i>	<i>Median water</i>	<i>SD water</i>	<i>Min. water</i>	<i>Max. water</i>
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 70: Descriptive statistics for overall life-cycle cost (online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Mean lccost</i>	<i>Median lccost</i>	<i>SD lccost</i>	<i>Min. lccost</i>	<i>Max. lccost</i>
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 71 shows that the treatment affects both 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% ($p < 0.05$).

Table 71: Effect on overall energy use, water and cost (online shop round 2)

	<i>ln(energy)</i>			<i>ln(water)</i>	<i>ln(lccost)</i>	
	(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-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. See figure 63 in appendix VIII for residual histograms.

The effect sizes (f^2) of all regressions reported above range from 0.0024 to 0.011 (see table 121 in appendix VIII).

4.5.2.4 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 mean price is higher in the treatment group (table 72)

The mean number of click-throughs is lower in the treatment group (table 73).

Table 72: Descriptive statistics for appliance prices (online shop round 2)

<i>All click-throughs</i>	<i>N</i>	<i>Sum price</i>	<i>Mean price</i>	<i>SD price</i>	<i>Min. price</i>	<i>Max. price</i>
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 73: Descriptive statistics for number of clicks per user (online shop round 2)

<i>All click-throughs</i>	<i>N users</i>	<i>Mean CT count</i>	<i>Median CT count</i>	<i>SD CT count</i>	<i>Min. CT count</i>	<i>Max. CT count</i>
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-throughs

The hypothesis that price and treatment are statistically independent cannot be rejected at a 5% level—but $p=0.050$ (see table 126 in appendix VIII). The hypothesis that the number of click-throughs and the treatment are independent is much harder to reject ($p=0.58$ —see table 125 in appendix VIII).

The tables below contain regression results for prices (table 74) and the number of click-throughs (table 75). When controlling for other factors, the treatment does not have an effect on prices nor click-throughs at a 5% level of significance.

Table 74: Effect on appliance prices (online shop round 2)

	(1) Simple search	<i>ln(price)</i> (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-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).

Table 75: Effect on the overall number of click-throughs (online shop round 2)

	<i>Count of click-throughs per user</i>
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).

4.5.3 Feedback forms

A total of 72 customers from the treatment group sent feedback to comment on the performance of the recommendation system.

Overall, 47% of respondents evaluated the system as “good” or “excellent”, whereas 51% rated it “less good” or “poor” (see figure 24 in appendix III). For each rating, customers provided detailed reasons. Among these reasons, the “result of the recommendation” was mentioned most often. The second most important reason was “user guidance” for those customers who gave a more positive rating overall, and “questions asked” for those who gave a more negative rating. A total of 11 customers mentioned “operating cost disclosure” as a reason, and all of them provided a positive rating overall (i.e. “good” or “excellent”). This positive evaluation of operating cost disclosure did not change markedly between experimental treatment rounds.

With respect to the recommendation agent’s effect, less than 10% of those customers who provided feedback actually bought the washing machine directly at the online shop. More than 40% stated that they found a machine, but just wanted to gather information, and did not buy the machine (see figure 25 in appendix III).

Only two out of 72 customers had already visited other websites that provide operating cost information for household appliances. A large majority responded with “No”, or did not answer the question at all (see figure 26 in appendix III).

Finally, many customers provided additional comments. Most were very specific and only partially helpful for a systematic future improvement of the recommendation system. None of them, however, referred to the operating cost feature in any way which

is why they are not relevant for this dissertation.

4.5.4 Telephone interviews

A total of five females and three males from all over Germany participated in the telephone interviews.

Five individuals had used the recommendation agent during the first experimental round, and three during the second. All of them had used the Simple search mode of the recommendation agent. The youngest individual was in his twenties, the oldest more than 60 years old. Concerning education, less than half of them had pursued graduate studies at a university. Nearly all of them were employed at the time of the interview, and nearly all of them had used the internet since the early or mid-1990s. Table 81 (appendix III) gives an overview of basic demographics of all participants, and table 82 contains the interview transcripts. In the following sections, I summarize the results sorted by the interview topics.

4.5.4.1 Reaction to, and understanding of the disclosed operating cost

Participants' initial reactions when seeing the disclosed operating cost for the first time ranged from astonishment to no reaction at all. One participant described operating cost disclosure as a matter of course, but admitted later that she did not look at the output from the recommendation agent in detail. Two of the participants from round two of the experiment could not remember having noticed the operating cost at all. Among these two, one explicitly explained that she was focusing on physical electricity and water use instead because cost figures were too much depending on prices, on which she had no influence at all. Most of the other participants described an initial astonishment when

seeing the operating cost.

One participant from the first round criticized the visual presentation of operating and life-cycle cost in round one as being too large and too dominant relative to other features. She also made clear that operating cost were much less important for her than the purchase price because operating cost occurred for all washing machines. Most participants understood the meaning of the disclosed operating cost.

4.5.4.2 Underlying assumptions, their adjustment, and role of energy prices

The underlying assumptions and their calculation were understandable for most participants. One of them mentioned that, at first, he and his wife did not understand that they were able to adjust the underlying assumptions in order to receive more suitable output from the calculation. Later on, however, they learned how to do this.

Another participant mentioned the importance of the online shop's reputation. He intuitively trusted the calculation because of his overall trust in the online shop. Therefore, he did not bother finding out more about the calculation and the underlying assumptions. Had it been another shop, he would not have trusted it as much.

One participant from the first round initially did not understand the underlying time horizon of the cost calculation, but later found out about it. One participant assumed that the default assumptions represented average values for German consumers. Overall, most of the participants did not adjust the default assumptions. One of them made clear that he did not know his exact local price of electricity or the local price of water. Another one stated that in his view, the default time horizon of nine years (in round two) was too short, and that it should be at least 10 to 12 years.

Potentially escalating energy prices were not an important factor for most participants.

4.5.4.3 Importance of energy efficiency for the participant

The technical efficiency of washing machines was of vital importance for nearly all participants. Some mentioned “water efficiency” or “energy efficiency” in particular whereas others did not specify what they were referring to exactly.

One participant explained that her way of choosing between appliances was to look for machines that carried the best or the second-best efficiency category label, that is “A” or “B”, respectively.

Two others cautioned that the water efficiency of a given machine should not be too low because this could lead to insufficient washing performance.

4.5.4.4 Knowledge of alternative information channels

Alternative information channels regarding the energy efficiency of appliances were mentioned by most participants. Two of them mentioned (offline) retailers, while two others referred to internet websites by themselves.

When asked specifically about alternative websites that provide operating cost information for appliances, only one participant remembered vaguely having heard about the existence of such a site. Nevertheless, he had not visited it. Instead, he had visited the site from his local electricity utilities. This pattern was also described by another participant who, in addition, had looked at the websites of appliance producers.

4.5.4.5 Personal opinion about the future of operating cost disclosure

Participants' personal opinion about the value and the future of operating cost disclosure differed widely. The lowest common denominator for most participants was to provide optional operating cost disclosure for continuously running appliances such as cooling appliances. Regarding other contexts, fewer participants were convinced of the usefulness of operating cost disclosure.

One of the participants from round two suggested that in the experiment, operating cost were displayed too early in the process.

Other appliances for which one or more participants deemed operating cost disclosure useful were computers, televisions, dish washers, dryers, and conventional light bulbs vis-à-vis compact fluorescent lights.

One participant recommended concentrating on the physical units instead of monetary units because the latter were depending on prices. Prices, in turn, could change too often so that monetary values could hardly give meaningful guidance for one's purchasing choice.

4.5.4.6 Further comments

Further comments from participants predominantly did not refer to operating cost disclosure in any way, with three exceptions: One participant underscored the importance of purchase price information and demanded a less prominent visual representation of operating cost. Another participant demanded an explanation for the default time horizon, and also suggested providing annualized cost information.

4.6 Discussion

The discussion will concentrate on the substantive experimental outcomes (4.6.1) and on user feedback (4.6.3). Threats to validity have, for the most part, already been dealt with in section 3.6 for the shopbot case. Any remaining issues concerning the online shop will be presented in section 4.6.2. Finally, user feedback will be discussed in section 4.6.3.

4.6.1 Experimental outcomes

My five research hypotheses referred to the treatment effect on energy use, water use, estimated life-cycle cost, appliance prices, and click-throughs.

Treatment effects on energy use were consistently negative in both experimental rounds (where significant at a 5% level). Surprisingly, no overall effect could be detected in round one although life-cycle costs were more prominent, and the sample size was larger than in round two. Therefore, the longer assumed time horizon in round two seems to have been decisive for the outcome.

Water use also got consistently reduced through the treatment. In both rounds, the effect amounted to a reduction of about 0.7%

The effect on life-cycle cost was positive in round one. A tacit assumption of life-cycle cost minimization through consumers would be hard to reconcile with such a finding.

Since life-cycle costs were not disclosed to the 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. Consequently, the life-cycle cost estimates in the two groups were asymmetric: based on user-adjusted

assumptions (treatment) versus non-adjusted default assumptions (control).

An alternative would have been to derive life-cycle cost from non-adjusted default assumptions for both groups. In such a comparison, none of the treatment coefficients would have been significant at a 5% level in round one (see table 112 in appendix VII) or round two (see table 124 in appendix VIII). In other words, the few positive effects on life-cycle cost were sensitive to the adjustment of assumptions in the treatment group (see table 110 in appendix VII, and table 122 in appendix VIII).

In terms of size, the treatment effect for energy use, water use, and life-cycle cost can be deemed “small” ($f^2=0.02$) (Cohen 1977, 413) (see table 109 in appendix VII, and table 121 in appendix VIII).

Given the online shop’s business model, the number of click-throughs and the prices of clicked appliances jointly matter for turnover. In round one, both effects were ambiguous and depended on capacity. In round two, no effect could be found in the regression analyses. Yet, the hypothesis of independence of treatment and price could nearly be rejected at a 5% level ($p=0.05$). Since the product of click-throughs and appliance prices—that is, the best available indicator of turnover—was lower in the treatment group, this finding suggests the possibility of a negative impact on retail volume. Regardless of the exact effect, both a neutral or negative effect constitute a barrier for private firms to adopt life-cycle cost disclosure by themselves—even if such a feature is beneficial regarding the detected decrease in energy use.

Lastly, including the price of gas in its current or lagged form as a covariate did not change the experimental results noticeably, if at all (for the price over time see figure 35 in appendix V). Therefore, these coefficient estimates are not reported explicitly.

In sum, the following treatment effects could be detected: first, a decrease in overall energy use by 0.83% in round two. Second, an overall increase in life-cycle cost by 1.4% in round one—which, however, is very sensitive to the assumptions used in the calculation of life-cycle cost. Third, a decrease in water use by about 0.7% in both experimental rounds. Fourth, an ambiguous or non-existing impact on retail volume which does not make life-cycle cost disclosure in the chosen format attractive by itself from a business perspective. The policy implications of the experimental findings will be discussed in section 5.2.

4.6.2 Validity

Most threats to validity discussed for the shopbot (3.6) also apply to the online shop experiment. Further issues have to do with external and measurement validity.

4.6.2.1 External validity

First, the clicking behavior of users may tell something about their spatial distribution. As described above (4.5.1), I discarded a high number of repeated click-throughs on the same product. These double-clicks seem to indicate user impatience because of low bandwidth internet connections and associated slow data flow. According to a recent survey, about half of all German internet users have high-speed internet access (van Eimeren and Frees 2006, 408). Since high bandwidth connections are less available in rural areas, it may be that the online shop attracts a relatively high proportion of users from those areas. It is unclear, however, in what way this could potentially bias the treatment effect.

Second, the washing machines offered in the online shop represent only a limited

subset of all products and brands available in the market. In the online shop, the range of washing machines (see table 105 in appendix VII) was smaller than what is available through shopbots like, for example, WEB.de. Moreover, products from only seven different brands were offered while WEB.de presents more than 20 brands. 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 (see 4.2). 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.

4.6.2.2 Measurement validity

Different from cooling appliances, 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 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 standardized appliance characteristics. Actual energy use or water use may be different

and depends on individual consumer behavior.

4.6.2.3 Summary of threats to validity

Table 76 below summarizes potential threats to validity.

Table 76: Summary of threats to validity (online shop)

<i>Cause</i>	<i>Potential bias</i>	<i>Effect on treatment outcome</i>	<i>Comment</i>
Use of cookies for randomization	Priming, imitation of treatment	–	Small given the relatively larger cognitive effort needed; Conservative bias
	Resentful demoralization of untreated	+	Unlikely given the real purchasing situation, otherwise problematic
Restricted range of products and brands offered	Restricted range of energy use	–	Limits generalizability
Co-existence of experimental recommendation agent and regular shopping interface within the same given online shop	Self-selection	?	Limits generalizability
Immeasurable characteristics of online shop (advertising, hyperlink structure, reputation)	Self-selection	?	Limits generalizability

4.6.3 User feedback

Feedback forms and qualitative interviews refer to opinions from consumers who self-selected into filling the form and being interviewed. These views can therefore shed light on certain issues but cannot be deemed representative of the population of online shoppers visiting the online shop.

While understanding life-cycle cost in general did not seem to be a problem, critical issues raised by interview respondents mainly referred to the visual presentation.

Two distinct forms of visual cost presentation were chosen in the two treatments rounds. In round one, all cost factors were integrated in one line whereas in round two, operating and life-cycle cost was disclosed in a separate line subsequent to the purchase price. Moreover, the treatment in round two encompassed an additional line showing the assumed time horizon, and an information button to explain how to adjust the underlying assumptions (see 4.4.1.1).

Responses from interview participants illustrate the principal problem with finding an adequate design for life-cycle cost disclosure. One participant from round one underscored the primacy of purchase price information and criticized the visual dominance of operating cost figures. His comment was one of the reasons why the treatment format was changed in the second round. Conversely, two participants from the second round could not remember having noticed the operating cost at all.

These reactions make clear that the choice of format involves difficult trade-offs. On the one hand, if consumers dislike a given visual format, their propensity to click-through may get reduced. Also, too many pieces of information may make the cognitive load too high. This is important when considering one respondent's comment who would also like to see annualized operating cost. On the other hand, information needs to be placed prominently enough to attract the attention of consumers who may be in an early screening stage of their purchasing process (Häubl and Trifts 2000, 7).

Another aspect of search behavior was described by one interview respondent. He explained that he was basically looking for a product that outperformed his old washing machine in terms of energy and water use. Another interview participant stated that he relied on efficiency labeling categories in making his choice. None of them mentioned

operating cost as a measuring rod. These comments indicate a tendency to not optimize economically, but to follow much simpler heuristics—a finding that would be consistent with an increase in life-cycle cost (see 4.5.1.3).

Chapter 5: Conclusions

5.1 Summary of experimental findings

Table 77 below summarizes all findings from the experimental life-cycle cost disclosure. In the shopbot, consumers clicked-through to final online retailers. In the online shop, they put appliances into the virtual shopping cart. Both forms of product-specific clicks were evaluated by means of multiple regression analysis.

Table 77: Summary of all treatment effects that are significant at a 5% level

<i>Dependent variables</i>	<i>Energy use</i> [kWh/unit ^b]		<i>Life-cycle cost^c</i> [Euro]		<i>Water use</i> [L/cycle]		<i>Impact on retail volume^d</i>	
	1	2	1	2	1	2	1	2
<i>Cooling appliances (shopbot)</i>								
Freezers	+/- ^e				n/a	n/a		
Fridge-freezers					n/a	n/a		
Refrigerators	-4.2%				n/a	n/a		
Overall	-2.5%				n/a	n/a	-23% ^f	
N (total)	1969	1391	1969	1391	1969	1391	1969	1391
<i>Washing machines (online shop)</i>								
Simple search mode	-1.2%	-0.81%					+/- ^e	
Expert search mode	-1.0 %		+2.7% ^g		-1.1 %	-0.97%		
Overall	-0.83%		+1.4% ^g		-0.72%	-0.74%	+/- ^e	
N (total)	2386	2065	2386	2065	2386	2065	2386	2065

Note: n/a: not applicable

- default time horizon for life-cycle cost estimation: 5 years (shopbot round 1), 9 years (shopbot round 2), 4.9 years (online shop round 1), 9 years (online shop round 2).
- unit: [year] for cooling appliances, and [cycle] for washing machines
- life-cycle costs were only shown to the treatment group and were therefore simulated for the control group based on default assumptions
- number of click-throughs (shopbot); combination of click-throughs and appliance prices (online shop)
- direction of the effect depends on appliance capacity
- not significant anymore and reduced to about -10% if previously discarded click-throughs (repeated clicks, potential robots) are included
- not significant anymore when life-cycle costs are estimated based on non-adjusted default assumptions for the treatment group, too.

Life-cycle cost disclosure consistently reduced energy use. The overall reduction in energy use ranged from 2.5% in the shopbot case (round 1) to 0.83% in the online shop (round 2). These reductions, however, refer to different treatments.

In the shopbot, the treatment consisted of placing life-cycle cost at a very prominent position; that is, in the same line and with equal font size as the purchase price. Moreover, operating cost was estimated based on a relatively short time horizon (5 years) that corresponds to a high implicit discount rate.

In the online shop, the reduction occurred in a setting in which life-cycle cost always appeared as secondary information with a smaller font size. Also, estimated operating cost figures were relatively larger because of the longer underlying time horizon (9 years) that reflected a lower implicit discount rate. Given these differences in treatment, the reductions in energy use cannot be directly compared between the shopbot and the online shop.

Life-cycle cost disclosure also reduced the overall water use of washing machines by about 0.7% in both experimental treatment rounds.

Despite those significant reductions in energy and water use associated with the treatment, estimated life-cycle costs were affected in only two cases. They represented increases in life-cycle cost for washing machines; but these increases were highly sensitive to the exact calculation of operating cost. When using common default assumptions for both experimental groups, no significant effects on life-cycle cost remained.

Only one unambiguous impact on retail volume could be detected—a reduction in click-throughs from the shopbot to final retailers by about 23%. This reduction coincided

with the reduction in energy use in round one of the experiment.

The assumptions regarding the underlying time horizon for operating cost estimation were rarely adjusted by users in the treatment group. In each experimental round, less than 5% of all treated users changed the default time horizon. In the shopbot case, users in the treatment group were also able to sort and filter product lists by life-cycle cost. Yet, less than 3% of them made use of these functions.

The last finding requires a comment. By definition, sorting and filtering by life-cycle cost would have considerably facilitated life-cycle cost minimization. Given the rare use of these functions, one may wonder how rational consumers' behavior actually was. Although my research hypotheses were motivated by different theoretical perspectives on decision-making, this dissertation could not answer the question whether consumers behave as rational optimizers, or whether they follow different heuristics. The reason is that empirically discriminating between optimizing and other patterns of behavior can be difficult (March 1994, 20). Methodologically, laboratory experiments facilitate differentiation because they allow for setting up specific decision alternatives. Such an artificial set up, however, was unfeasible in the field experiment described here. Under these field conditions, a better identification of consumer actions would have required comprehensive knowledge of all product attributes. Given the lack of data with respect to several characteristics, I did not attempt to identify a particular kind of consumer behavior.

All in all, the evidence suggests that life-cycle cost disclosure has an effect on consumer behavior. It leads individuals to opt for more energy-efficient cooling appliances and washing machines. Similarly, it stimulates the choice of more water-

efficient washing machines. Both effects make life-cycle cost disclosure a potentially interesting approach for environmental policy. From a business perspective, however, implementing life-cycle cost disclosure offers no direct benefits because it goes along with a negative or neutral impact on retail volume.

5.2 Policy implications

Whether the effects reported here are substantively important from a policy perspective is primarily a question about costs and benefits. Both costs and benefits of life-cycle cost disclosure depend on the scale of its implementation.

Maximum scale would necessitate that life-cycle cost become an integral part of mandatory energy-efficiency labels. Given the static character of conventional labels, however, consumers would not be able to individually adjust the underlying assumptions. On the other hand, the experimental findings reported above suggest that only a small fraction of consumers would be interested in changing the default assumptions anyway. In any case, integrating life-cycle cost into mandatory labels requires a high degree of consensus regarding the default assumptions used. Moreover, it is unclear to what extent the treatment effects from the online experiments reported here are applicable to purchasing situations in physical stores that include interactions with sales personnel. Those are the problems associated with implementing life-cycle cost disclosure at maximum scale.

A smaller solution would be to implement life-cycle cost disclosure merely on the internet. Although online sales of large household appliances are growing, their share in total German sales quantity was below 10% in 2004 (Gesellschaft für Konsumforschung

2005). Still, for electronic commerce across all product categories, about 50% of all Germans report having incorporated available online information into their purchasing process, and about 45% of all Germans deem price comparisons to be the single most important element (Nielsen/Netratings 2004; van Eimeren, Gerhard et al. 2004). These figures demonstrate that the internet and price comparisons are important for the purchasing process even if the final purchase itself still occurs predominantly in physical stores.

Providing life-cycle cost on the internet could be pursued through voluntary initiatives. The largest obstacle to such initiatives would probably be the missing direct business incentive for implementation. Still, voluntary life-cycle cost disclosure may be publicly supported by non-governmental organizations. Implementation could therefore prove to be at least indirectly beneficial in terms of public relations.

5.2.1 Costs of life-cycle cost disclosure

Determining the costs of implementing life-cycle cost disclosure in detail is beyond the scope of this dissertation. Instead, I will only raise key issues concerning the possible implementation options.

Option one—the mandatory, large-scale labeling approach—is associated with high information requirements that may make it prohibitive. Life-cycle cost information as defined in this dissertation consists of lifetime operating costs and product retail price. While the former can be supplied by manufacturers, the latter is only known to retailers. Providing information about both cost components therefore involves several actors. This, however, would be a departure from current US and EU labeling systems which

predominantly rely on manufacturers' information about product characteristics (du Pont, Schwengels et al. 2005, 112). Such a more than incremental change in the labeling system is, therefore, likely to involve considerable cost.

A possible alternative that comes closest to full life-cycle cost disclosure would be the provision of lifetime operating cost; that is, operating cost estimated over the entire lifetime of a given appliance. Consumers would then need to add these costs to the product price by themselves if they wanted to determine life-cycle cost.

The effect of lifetime operating cost disclosure, however, cannot be directly inferred from this dissertation because its focus was on the provision of *both* lifetime operating cost and life-cycle cost. Consequently, it cannot answer the question whether the disclosure of lifetime operating cost on its own would lead to similar results. The results may in fact differ, given the cognitive effort associated with adding price and lifetime operating cost manually. Still, the results may indicate the overall direction of the effect. Lifetime operating cost provision is currently under discussion in the US and the European Union (see 2.4.5).

All in all, the costs of implementing changes to mandatory labels depend on the institutional setting and the number of actors involved. If additions to the label could be easily linked with planned label revisions or updates, the incremental costs of implementation might be relatively small. Otherwise, costs would be much larger.

The second option, voluntary life-cycle cost disclosure on the internet, may also vary in terms of implementation cost. In the European Union, all vendors of household appliances are mandated to supply energy use information with the label anyway—data that is necessary for estimating life-cycle cost. The only restriction, then, is technical in

nature: digital product information can be available in separate database fields, or it can be part of an encompassing string variable. With separate data fields, implementing life-cycle cost disclosure should be relatively inexpensive. In the latter case, however, the opposite would be true. Extracting specific information from string variables is prone to errors. Only a future standardization in electronic product catalogues might lower this hurdle.

These general considerations show that both possible approaches for implementation—large-scale and small-scale—may come at different cost.

5.2.2 Benefits of life-cycle cost disclosure

Understanding potential benefits requires looking at the estimated amount of CO₂ under consideration, and the associated value.

Table 127 in appendix IX contains order-of-magnitude estimates for potential CO₂ reductions in Germany through life-cycle cost disclosure. The key assumption is a large-scale mandatory implementation of the disclosure on all energy efficiency labels for household appliances. Starting from this assumption, the total amount of CO₂ mitigated would be in the range of 10 to 20 thousand metric tons per year—that is, less than 0.01 percent of Germany's total anthropogenic CO₂ emissions of 853 million tons in 2000 (EWI 2005).

The monetary benefits of such an emission reduction would depend on the value of a ton of CO₂. According to current predictions for Germany which assume a moderate climate policy for the years to come, tradable permits for CO₂ may cost up to 15 EUR(2000)/t CO₂ until 2030 (EWI 2005).

Multiplying expected permit cost and CO₂ reductions leads to maximum benefits in the range of 150,000 to 300,000 EUR(2000)/year. These figures represent an upper bound for the benefits that can be expected from a large-scale implementation of life-cycle cost disclosure in Germany. Analogously, a voluntary implementation on the internet would lead to smaller maximum benefits. They would depend on how many websites participate in the disclosure, and on how the market share of online appliance purchases develops over time.

The preceding quantification of benefits neglected two aspects. First, I disregarded potential savings in water use through more efficient washing machines and dishwashers. Second, I did not attempt to quantify second order effects induced by life-cycle cost disclosure. It may well be that this form of monetary cost presentation stimulates long-term learning processes on the part of consumers. But it would be hard to evaluate those effects in any kind of field experiment—which was the focus of this dissertation.

All things considered, if life-cycle disclosure for household appliances can be institutionalized at relatively low cost, it may have tangible benefits. Yet, the magnitude of the figures derived here indicates that potential benefits may not justify a complex bureaucratic realization.

This analysis does not provide an argument against energy labeling as such. It simply cautions that the incremental effect of adding monetary information to existing energy labels may not pass a simple cost-benefit test. In such a case, investing in alternative CO₂ reduction measures and related policies may be more valuable.

Still, the estimation of benefits presented here is based on static assumptions.

Future changes in energy prices may lead to larger effects of life-cycle cost disclosure on consumer behavior. Other than that, several aspects of life-cycle cost disclosure should be further examined in the future.

5.3 Avenues for future research

Apart from clarifying the implementation cost of life-cycle cost disclosure, avenues for future research have to do with the generalizability of my findings, with database completeness, the instruments used, the time horizon, the framing of cost information, and new information technology.

First of all, external validity would generally benefit from conducting similar experiments in other countries with different energy cost, water cost and existing efficiency labeling systems. In principle, the scope of experimental life-cycle cost disclosure could also be extended to other energy-consuming durable goods such as cars.

Second, more complete databases will provide a better understanding of consumer decision-making. In the shopbot experiment described here, not every final retailer revealed his shipping costs. Consequently, these costs could not be integrated into the calculation of life-cycle cost without reducing the shopbot's functionality. In this regard, future life-cycle cost experiments in shopbots should strive for data completeness as much as possible.

Third, the instruments described in this dissertation are click-throughs. They describe actual consumer behavior, but cannot provide a description of final purchasing choices. In the shopbot, no obligation for consumers whatsoever resulted from clicking-through to final retailers. The same is true for the products that consumers put into the

virtual shopping cart of the online shop. Due to a lack of integration in software systems, however, purchase data could not be collected as part of this project. Therefore, the final step in the cause-and-effect chain from information disclosure to consumer action is still missing.

The problem is that there may be a systematic difference in behavior between the treatment and the control group. Two opposite effects are conceivable. On the one hand, treated consumers may, on average, feel better informed through life-cycle cost disclosure. They may feel more confident about the kind of appliance they want to buy. On the other hand, being confronted with life-cycle cost information may be surprising or demanding for some consumers. It may stimulate doubts and induce a longer search for alternatives. In such a case, the short term effect of life-cycle cost disclosure shown here may get diffused over the course of the extended product search. These opposed scenarios call for research on life-cycle cost disclosure that actually measures the final purchasing decision.

Fourth, future research should examine differences in information format. Various alternative formats are thinkable for presenting monetary information to consumers: as yearly operating cost, lifetime operating cost, life-cycle cost, and annualized life-cycle cost. Each format could be evaluated relative to the others. Annualized cost may have an exposed position compared to other figures if consumers can better plan their expenditures on such a basis.

Fifth, what has not been assessed in the context of energy cost disclosure so far is the framing of the cost information. Loss aversion (Kahneman and Tversky 1979) may lead individuals to assess gains and corresponding losses asymmetrically. That is, energy

cost savings may be evaluated differently than surcharges of the same amount. Life-cycle cost disclosure as such usually aims at presenting the true long-run cost of a given appliance, and this is predominantly done by presenting additional *cost* information. Consequently, it would be worth evaluating monetary information disclosure that represents operating cost of a more energy efficient model as cost *savings* compared to more inefficient reference models. Such a procedure, of course, assumes that information about comparable models and related savings is sufficiently available.

Sixth, one should evaluate the disclosure of life-cycle cost in conjunction with environmental information. With more and more governmental and non-governmental institutions planning on making CO₂-related information available for products and services, the question is whether this information disclosure has any effect. While life-cycle cost information as defined here refers to private cost, environmental information for the most part represents external cost. The question is whether these two pieces of information can be meaningfully integrated so that consumers can process them cognitively, and so that the information has an effect on consumer purchasing behavior.

Finally, in extending Lund's (1978) vision of computer-based decision-support for life-cycle cost disclosure, one can even think beyond the internet. For consumers, the future holds the increased use of information systems in conjunction with Radio Frequency Identification (RFID) at the point of sale (Strüker, Sackmann et al. 2004). These systems would combine in-store appliance energy characteristics with interactive adjustment of life-cycle cost estimates through consumers. And they would allow for a new kind of sales field evaluation.

Appendix I: shopbot screenshots

Figure 4: Flow chart of experimental process for the shopbot

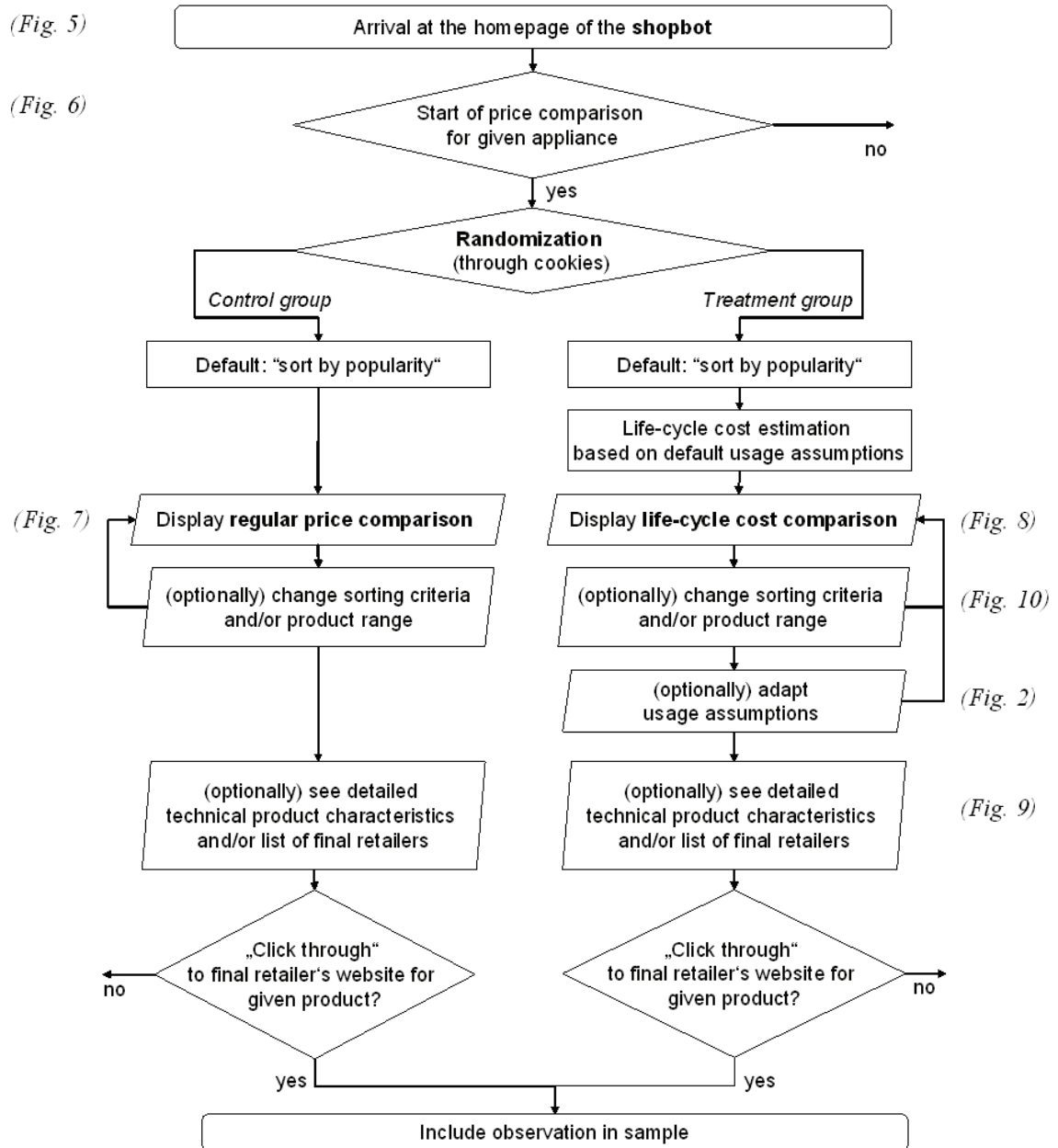



Figure 5: Introductory web page of the shopbot

Figure 6: Cooling appliance website of the shopbot

Figure 7: Product list in the shopbot's control group sorted by popularity

↶
Produktvergleich

A - Z | Preis | ▼ Popularität




Liebherr GP 1356 Premium

369,00 € bei [karstadt.de](#) i

Gefrierschrank 101l 189.8kWh/Jahr Effizienzklasse A+
gesamter Nutzinhalt: 101 l · Bau... [mehr](#)

Jetzt 15 Angebote im Preisvergleich oder bei ebay.




Liebherr GN 2153-20 No Frost

619,00 € bei [otto.de](#) i

Gefrierschrank 184l 277.4kWh/Jahr Effizienzklasse A
gesamter Nutzinhalt: 184 l · Baua... [mehr](#)

Jetzt 17 Angebote im Preisvergleich oder bei ebay.



Liebherr GN 2553-20 NoFrost

585,00 € bei [ihre-topp-preise.de](#) i

Gefrierschrank 220l 303kWh/Jahr Effizienzklasse A
gesamter Nutzinhalt: 220 l · Baua... [mehr](#)

Jetzt 14 Angebote im Preisvergleich oder bei ebay.

Kein
Bild

Robert Bosch GSN 28A20

649,00 € bei [promarkt.de](#) i

Gefrierschrank 255l 288kWh/Jahr Effizienzklasse A+
gesamter Nutzinhalt: 255 l · Bau... [mehr](#)

Jetzt 15 Angebote im Preisvergleich oder bei ebay.

WEB.DE SmartSearch®

Kategorie wechseln
Gefrierschränke

Hersteller

- AEG (57)
- Liebherr (37)
- Miele (24)
- Robert Bosch (45)
- Siemens-Electr. (28)

[mehr](#)

Preis

- unter 300 € (39)
- 300 € - 400 € (48)
- 400 € - 450 € (30)
- 450 € - 500 € (31)
- 500 € - 600 € (43)

[mehr](#)

gesamter Nutzinhalt


- Min. 100l (163)
- Min. 150l (134)
- Min. 200l (90)
- Min. 250l (34)
- Min. 300l (11)

Energie-Effizienz-Klasse

Bauarten

Figure 8: Product list in the shopbot's treatment group sorted by popularity

Produktvergleich
A - Z | Preis | Gesamtkosten | ▼ Popularität




Liebherr GP 1356 Premium
369,00 € bei [karstadt.de](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
642,31 €	=	369,00 €	+	273,31 €

Gefrierschrank 101l 189.8kWh/Jahr Effizienzklasse A+
gesamter Nutzinhalt: 101 l · Bau... [mehr](#)

Jetzt 15 Angebote im Preisvergleich oder bei ebay.




Liebherr GN 2153-20 No Frost
592,00 € bei [edelguenstig.de](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
991,46 €	=	592,00 €	+	399,46 €

Gefrierschrank 184l 277.4kWh/Jahr Effizienzklasse A
gesamter Nutzinhalt: 184 l · Baua... [mehr](#)

Jetzt 17 Angebote im Preisvergleich oder bei ebay.




Liebherr GN 2553-20 NoFrost
585,00 € bei [ihre-topp-preise.de](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
1.021,32 €	=	585,00 €	+	436,32 €

Gefrierschrank 220l 303kWh/Jahr Effizienzklasse A
gesamter Nutzinhalt: 220 l · Baua... [mehr](#)

Jetzt 14 Angebote im Preisvergleich oder bei ebay.



Kein
Bild

Robert Bosch GSN 28A20
649,00 € bei [promarkt.de](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
1.063,72 €	=	649,00 €	+	414,72 €

WEB.DE SmartSearch®

Kategorie wechseln
Gefrierschränke

Hersteller

- AEG (57)
- Liebherr (37)
- Miele (24)
- Robert Bosch (45)
- Siemens-Electr. (28)
- [mehr](#)

Gesamtkosten

- unter 500 € (9)
- 500 € - 600 € (28)
- 600 € - 700 € (27)
- 700 € - 800 € (55)
- 800 € - 900 € (44)
- [mehr](#)

Preis

- unter 300 € (39)
- 300 € - 400 € (48)
- 400 € - 450 € (30)
- 450 € - 500 € (31)
- 500 € - 600 € (43)
- [mehr](#)


gesamter Nutzinhalt

Energie-Effizienz-Klasse

Bauarten

Figure 9: Price comparison for sample freezer in the shopbot's treatment group

Produktdetails



[größeres Bild](#)

AEG ARCTIS 75 230 GA


Gefrierschrank 215l 281kWh/Jahr Effizienzklasse A+
 gesamter Nutzinhalt: 215 l · Bauarten: Standgerät > 85 cm ·
 Energie-Effizienz-Klasse: A Plus

Gesamtkosten = Preis + [Betriebskosten](#) (404,64 €)

10 Angebote gefunden

Gesamtkosten:
962,64 € bis 1.203,64 €

Preis:
558,00 € bis 799,00 €

oder bei  finden

[PreisCheck](#)
[Datenblatt](#)

In diesen Angeboten suchen: [Go](#) 1 - 9 von 9 Shops mit insg. 10 Angeboten.

[Verfügbar](#)
[Preis](#)
[Shops](#)









<p>AEG Arctis 75230 GA Gefrierschrank noFrost</p> <p>TOP-KLASSE Energie-Effizienzklasse: A+ Energieverbrauch: 281 kWh/Jahr Tür im charakteristischen 3-D-Design QUICK-Türöffner - für leichtes Türöffnen Wenn Sie bei herkömmlichen großen Kältegeräten die Tür öffnen, merken Sie vor allem eins: Widerstand ... mehr</p> <p>Verfügbarkeit: 7-10 Werktage · Versandkosten: siehe Shop</p>	 normal verfügbar	664,30 €	 Shop-Info Zum Shop
<p>AEG Gefrierschrank Arctis 75230 GA</p> <p>Verfügbarkeit: Sofort lieferbar! · Versandkosten: 59</p>	 sofort verfügbar	595,00 €	 Shop-Info Zum Shop
<p>AEG Arctis 75230 GA db</p> <p>Verfügbarkeit: awaiting · Versandkosten: siehe Shop</p>	 schlecht verfügbar	636,00 €	 Shop-Info Zum Shop
<p>AEG Arctis 75230 GA - Gefrierschrank</p>			

Figure 10: Life-cycle cost sorting and filtering in the shopbot's treatment group

Produktvergleich
A - Z | Preis | **▲ Gesamtkosten** | Popularität




Privileg 248
349,95 € bei [quelle.de](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
482,43 €	=	349,95 €	+	132,48 €

Kühlschrank 243l 92kWh/Jahr Effizienzklasse A+ gesamter Nutzinhalt: 243 l · Bauart... [mehr](#)

Jetzt 2 Angebote im Preisvergleich oder bei [ebay](#).




Beko SSE 26000
279,00 € bei [karstadt.de](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
519,48 €	=	279,00 €	+	240,48 €

Kühlschrank 256l 167kWh/Jahr Effizienzklasse A gesamter Nutzinhalt: 256 l · Bauarte... [mehr](#)

Jetzt 3 Angebote im Preisvergleich oder bei [ebay](#).



Bauknecht KRA 2010
293,99 € bei [eas-y.de/ruether/](#)

Betriebskosten geschätzt für 9 Jahre

Gesamtkosten	=	Preis	+	Betriebskosten
525,83 €	=	293,99 €	+	231,84 €

Kühlschrank 202l 161kWh/Jahr Effizienzklasse A gesamter Nutzinhalt: 202 l · Bauarte... [mehr](#)

Jetzt 3 Angebote im Preisvergleich oder bei [ebay](#).

WEB.DE SmartSearch@

Kategorie wechseln
Kühlschränke

gesamter Nutzinhalt [\[aufheben\]](#)
· Min. 200l

[Auswahl zurücksetzen](#)

Hersteller

- AEG (33)
- Gorenje (19)
- Liebherr (33)
- Robert Bosch (39)
- SMEG (24)
- [mehr](#)

Gesamtkosten

- 450 € - 600 € (12)
- 600 € - 700 € (25)
- 700 € - 800 € (29)
- 800 € - 900 € (31)
- 900 € - 1200 € (62)
- [mehr](#)

Preis

- unter 300 € (7)
- 300 € - 350 € (7)
- 350 € - 450 € (24)
- 450 € - 500 € (28)
- 500 € - 600 € (35)
- [mehr](#)

Bauarten

Energie-Effizienz-Klasse

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Figure 11: Detailed product comparison in the shopbot's treatment group

Produktvergleich			
Angezeigte Produkte	3	4	5
<p>1 2 3 4 5</p> <p>Produkte hinzufügen</p>	<p>Liebherr KTP 1740 Premium</p>  <p>PreisCheck</p> <p>[entfernen]</p>	<p>Gorenje RB 3122 W</p>  <p>PreisCheck</p> <p>[entfernen]</p>	<p>AEG Zanussi ZI 9155 A</p>  <p>PreisCheck</p> <p>[entfernen]</p>
Gesamtkosten			
min. Gesamtkosten	495,96 €	514,36 €	466,00 €
max. Gesamtkosten	594,95 €	567,35 €	596,00 €
Preis			
min. Preis	375,00 €	199,00 €	250,00 €
max. Preis	473,99 €	251,99 €	380,00 €
Konstruktion			
Bauarten	Tischgerät <= 85 cm	Standgerät > 85 cm	Einbaugerät
Konstruktion	Stellfüße vorn und	Höhenverstellbare	Variable Türausstattung,
Zusatzinformation	Transportrollen hinten; Attraktives SwingDesign	Vorderfüße	Antibakterielle Beschichtung im Innenraum
Türmechanismus	k.A.	k.A.	Schlepptür
Technik			
Energieverbrauch	84 kWh/Jahr	219 kWh/Jahr	150 kWh/Jahr
Energie-Effizienz-Klass	A++	A	A
Klimaklasse	SN	k.A.	k.A.
gesamter Nutzinhalt	150 l	120 l	154 l
automatische Abtauung	Ja	Ja	Ja
Gefrierfach Nutzinhalt	k.A.	17 l	k.A.

Appendix II: online shop screenshots

Figure 12: Flow chart of experimental process for the online shop

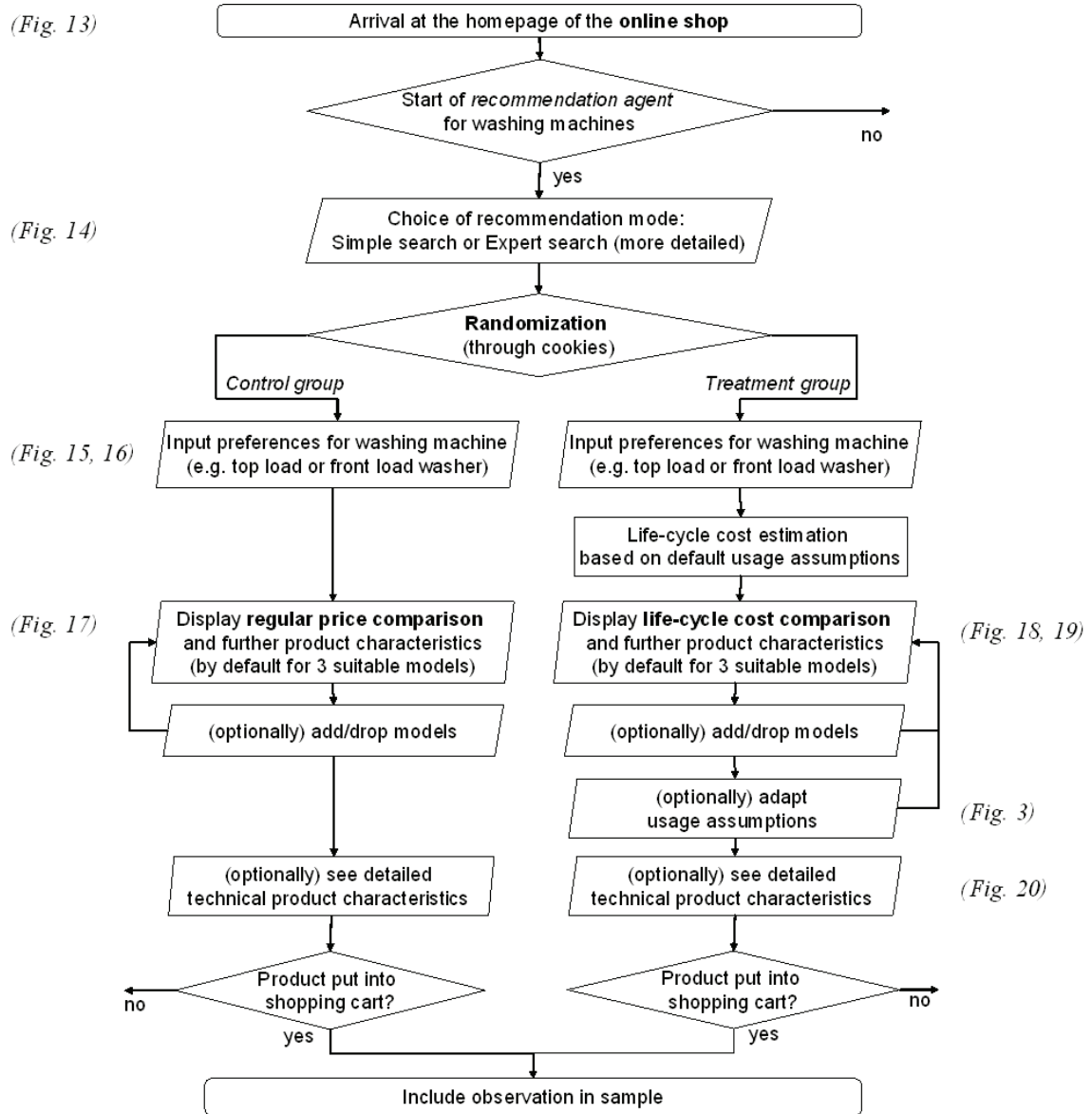


Figure 13: Introductory web page for washing machines in the online shop

QUELLE
www.quelle.de

Entdeckt, bestellt bei quelle.de

Mein Warenkorb Artikel: 0 Summe: 0.00 €
direkt zur Kasse

Home Aktuelles Mode Mode Baby, Kind Technik & Multimedia Haushaltsgeräte Wohnen & Haushalt Auto, Haus & Garten Sport, Reisen & Freizeit Schmuck & Uhren Geschenke & Blumen Schnäppchen & Auktionen

Sie sind hier: > Haushaltsgeräte > für Überblick > Waschen & Trocknen > Multimedia

Suche: Bitte Produkt oder Bestellnr. eingeben [Meine Quelle](#) | [Login](#)

Im Überblick

- Top 10
- Neuheiten (37)
- Waschen & Trocknen (148)**
 - Frontlader (65)
 - Toplader (27)
 - Trockner (51)
 - Spar-Set: Waschmaschine & Trockner (3)
 - Waschtrockner (5)
 - Schleudern (3)
 - Waschmaschinenberater
 - Problemlöser (11)
 - Sicherheitstipps
 - Trocknerinfo
- Kochen & Spülen (76)
- Kühlen & Gefrieren (200)
- Einbaugeräte (225)
- Elektrokleingeräte (516)
- Küchen-QUELLE

Markenwelten

Themen

Beratung & Service

Online Kataloge blättern

Waschen & Trocknen

PRIVILEG Express 6312
Waschvollautomat

€ 399.95

Frontlader

PRIVILEG
Waschvollautomat 33206
ab € 349.95

Toplader

Toplader 220 S
ab € 349.95

Trockner

PRIVILEG 9750 WP
Kondentrockner
€ 849.95

Alle Preise inklusive gesetzlicher MwSt. und zzgl. Service- & Versandkosten

Katalog-Besteller

Direkt bestellen aus Katalogen

- Kataloge gratis anfordern
- Online Kataloge blättern

Meine Services

- Ihre Traumküche
- Versicherungen & Finanzen
- Quelle Vodafone
- Foto Service

Meine Services

- Newsletter bestellen
- Meine Favoriten
- Mobile Services

Figure 14: Recommendation agent's start menu: choice between two systems

QUELLE
www.quelle.de

Entdeckt, bestellt bei quelle.de

Mein Warenkorb Artikel: 0 Summe: 0.00 €
direkt zur Kasse

Home Aktuelles Mode Mode Baby, Kind Technik & Multimedia Haushaltsgeräte Wohnen & Haushalt Auto, Haus & Garten Sport, Reisen & Freizeit Schmuck & Uhren Geschenke & Blumen Schnäppchen & Auktionen

Sie sind hier: > Haushaltsgeräte > für Überblick > Waschen & Trocknen > Multimedia

Suche: Bitte Produkt oder Bestellnr. eingeben [Meine Quelle](#) | [Login](#)

Im Überblick

- Top 10
- Neuheiten (37)
- Waschen & Trocknen (148)**
 - Frontlader (65)
 - Toplader (27)
 - Trockner (51)
 - Spar-Set: Waschmaschine & Trockner (3)
 - Waschtrockner (5)
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 - Waschmaschinenberater
 - Problemlöser (11)
 - Sicherheitstipps
 - Trocknerinfo
- Kochen & Spülen (76)
- Kühlen & Gefrieren (200)
- Einbaugeräte (225)
- Elektrokleingeräte (516)
- Küchen-QUELLE

Markenwelten

Themen

Beratung & Service

Online Kataloge blättern

Ihr persönlicher QUELLE-Waschmaschinen-Berater

Neue Waschmaschine? Wir beraten Sie.

Sie wissen noch nicht, welche Waschmaschine zu Ihnen passt?
Mit unserem [Waschmaschinen-Berater](#) führen wir Sie schrittweise zu Ihrer neuen Waschmaschine. Genau auf Ihre Anforderungen zugeschnitten, zeigen wir Ihnen eine passende Auswahl an Geräten

[zur Geräte-Beratung](#)

Sie wissen ziemlich genau, was Ihre neue Maschine können muß?
Toplader oder Frontlader, Fassungsvermögen, Schleudertouren u.v.m. Über zukunftsweisende Technik sind Sie bereits informiert. Dann finden Sie sicher in unserer [Profiauswahl](#) die richtige Maschine.

[zur Profiauswahl](#)

Figure 15: Preference elicitation in the online shop's Simple search mode

QUELLE-Berater / »Waschmaschinen suchen ein Zuhause«

1. Wie möchten Sie zukünftig waschen?

Ihre alte Waschmaschine hat ausgedient und ein Neukauf steht bevor? Dann sind Sie bei uns genau richtig! Wir bieten Ihnen eine kompetente Beratung. Nennen Sie uns Ihre Anforderungen...







<p>Platz sparen! Sie haben wenig Platz? Diese Waschmaschinen sind echte Problemlöser für mehr Platz in Bad und Küche. Klein und kompakt stehen Sie den Großen in nichts nach.</p>	<p>Eine für alles! Ausdauernd und waschwütig begleiten Sie diese Waschmaschinen durch den stressigsten Alltag. Sagen Sie schmutziger Wäsche den Kampf an!</p>	<p>Komfort pur! Einfache Bedienung, übersichtliches Display und maximale Sicherheit sprechen für diese Wahl. Holen Sie sich den bedienerfreundlichen Waschsalon nach Hause!</p>
<input checked="" type="radio"/> Auswählen	<input type="radio"/> Auswählen	<input type="radio"/> Auswählen

2. In welchem Preisrahmen möchten Sie sich bewegen?

nebensächlich
bis 400 €
400 - 600 €
600 - 800 €
800 - 1400 €

3. Haben Sie konkrete Anforderungen?

Größe des Haushalts?

▼
nebensächlich

Aufstellungsort?

▼
nebensächlich

Hersteller?

▼
nebensächlich

→ **Beratung starten**

Table 78: Answer options in the pull-down menus of the Simple search mode

Question Option	“Größe des Haushalts?”	“Aufstellungsort?”	“Hersteller?”
1	“nebensächlich”	“nebensächlich”	“nebensächlich”
2	“1-2 Personen”	“Keller oder Waschküche”	“AEG”
3	“3-4 Personen”	“Küche oder Bad”	“Bosch”
4	“größerer Haushalt”		“Matura”
5			“Miele”
6			“Privileg”
7			“SILENTIC”
8			“Siemens”

Figure 16: Preference elicitation in the online shop’s Expert search mode

QUELLE-Berater /»Waschmaschinen suchen ein Zuhause«

Hier finden Sie Ihre Neue!



Um Sie bei Ihrer Suche unterstützen zu können, benötigen wir Ihre individuellen Anforderungen an das Gerät. Wählen Sie selbst.

1. Ihre Angaben zu Preis und Hersteller.

minimaler Preis?	maximaler Preis?	Hersteller?
<input style="width: 90%;" type="text" value="0"/>	<input style="width: 90%;" type="text" value="1400"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>

2. Ihre Anforderungen an...

Fassungsvermögen?	Schleudertouren?	Zusatzprogramme?
*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>
Sicherheit?	Energie-Effizienz-Klasse?	Wasserverbrauch?
*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>

3. Haben Sie weitere Wünsche?

Bauart?	Bauform?	Platzprobleme?
*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>	*** bitte wählen *** <input style="width: 20px;" type="button" value="v"/>

→ Suche starten

Table 79: Answer options in the pull-down menus of the Expert search mode

<i>Question</i>	<i>“Hersteller?”</i>		
<i>Option</i>			
1	“bitte wählen”		
2	“AEG”		
3	“Bosch”		
4	“Matura”		
5	“Miele”		
6	“Privileg”		
7	“Siemens”		
8	“SILENTIC”		

<i>Question</i>	<i>“ Fassungsvermögen?”</i>	<i>“Schleudertouren?”</i>	<i>“Zusatzprogramme?”</i>
<i>Option</i>			
1	“bitte wählen”	“bitte wählen”	“bitte wählen”
2	“mindestens 4 kg”	“mindestens 1000 U/min”	“Beladungserkennung”
3	“mindestens 5 kg”	“mindestens 1200 U/min”	“prog. Timer”
4	“mindestens 6 kg”	“mindestens 1400 U/min”	“Schaumkontrolle”
5		“mindestens 1600 U/min”	“Wolleschonung”
6			“Energiesparfunktion”

<i>Question</i>	<i>“Sicherheit?”</i>	<i>“Energie-Effizienz-Klasse?”</i>	<i>“Wasserverbrauch?”</i>
<i>Option</i>			
1	“bitte wählen”	“bitte wählen”	“bitte wählen”
2	“Kindersicherung”	“mindestens A plus”	“höchstens 40 Liter”
3	“Wasserschutz”	“mindestens A”	“höchstens 45 Liter”
4	“Wasserstopp”	“mindestens B”	“höchstens 50 Liter”

<i>Question</i>	<i>“Bauart?”</i>	<i>“Bauform?”</i>	<i>“Platzprobleme?”</i>
<i>Option</i>			
1	“bitte wählen”	“bitte wählen”	“bitte wählen”
2	“Toplader	“Unterbaugerät”	“geringe Breite (bis 50 cm)”
3	“Frontlader”		“geringe Tiefe (bis 50 cm)”
4			“geringe Höhe (bis 70 cm)”

Figure 17: Simple search recommendations in the online shop's control group

QUELLE-Berater/»Waschmaschinen suchen ein Zuhause«

Ihre Eingaben waren: ▶ [Eingaben ändern](#)
 Eine für alles! / Preis: nebensächlich ▶ [zurück / neu starten](#)

Unsere Waschmaschine für Sie...



[Bild vergrößern](#)

[Vergleich](#)

Miele W 4146 WPS
 Leistungsstark und zuverlässig.

Auf einen Blick
 Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.

1.159,95 €

▶ [Produktdetails anzeigen](#) → in den Warenkorb legen!

▶ [Wie gut passt dieses Produkt zu Ihren Anforderungen?](#) →

▶ [Dürfen wir Ihnen andere Waschmaschinen empfehlen?](#)

... und mögliche Alternativen! Seite 1 2 3



[Bild vergrößern](#)

[Vergleich](#)

Privileg Dynamic76606
 Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.

699,95 €

▶ [Produktdetails anzeigen](#) → in den Warenkorb legen!

▶ [Wie gut passt dieses Produkt zu Ihren Anforderungen?](#) →

Figure 18: Simple search recommendations in the online shop's treatment group

QUELLE-Berater/»Waschmaschinen suchen ein Zuhause«

Ihre Eingaben waren: ▶ [Eingaben ändern](#)
 Eine für alles! / Preis: nebensächlich ▶ [zurück / neu starten](#)

Unsere Waschmaschine für Sie...



[Bild vergrößern](#)

Miele W 4146 WPS
Leistungsstark und zuverlässig.

Auf einen Blick
Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.

1.159,95 €

Betriebskosten (bei 9,0 Jahren Nutzung)

Gesamtkosten	= Preis	+ <u>geschätzte Betriebskosten</u>
1.649,74 €	= 1.159,95 €	+ 489,79 €

▶ [Produktdetails anzeigen](#) → in den Warenkorb legen!

▶ [Wie gut passt dieses Produkt zu Ihren Anforderungen?](#) →

[Vergleich](#)

▶ [Dürfen wir Ihnen andere Waschmaschinen empfehlen?](#)

... und mögliche Alternativen!

Seite 1 2 3



[Bild vergrößern](#)

Privileg Dynamic76606
Energiesparende Waschmaschine (Energie-Effizienz-Klasse A Plus), bei 1600 U/min eine extrem große Schleuderwirkung, Waschwirkungsklasse A, großes Fassungsvermögen (6 kg) mit automatischer Beladungserkennung. Mit Wolleschonungsprogramm.

699,95 €

Betriebskosten (bei 9,0 Jahren Nutzung)

Gesamtkosten	= Preis	+ <u>geschätzte Betriebskosten</u>
1.145,37 €	= 699,95 €	+ 445,42 €

▶ [Produktdetails anzeigen](#) → in den Warenkorb legen!

▶ [Wie gut passt dieses Produkt zu Ihren Anforderungen?](#) →

[Vergleich](#)

Figure 19: Expert search recommendations in the online shop's treatment group

QUELLE-Berater/»Waschmaschinen suchen ein Zuhause«

Ihre Eingaben waren:
Preis: 0,00 € - 1.400,00 €

[Eingaben ändern](#)

[zurück / neu starten](#)

Ihre Auswahl:

	<p>Privileg Basic 78 800</p> <p>Fassungsvermögen: 4,5 kg / Maximale Schleudertouren: 800 U/min / Wasserverbrauch: 62 l</p> <p>249,95 €</p> <p>Betriebskosten (bei 9,0 Jahren Nutzung)</p> <p>Gesamtkosten = Preis + <u>geschätzte Betriebskosten</u></p> <p>825,17 € = 249,95 € + 575,22 €</p>	<input type="checkbox"/>
	<p>Privileg Basic 88</p> <p>Fassungsvermögen: 4,5 kg / Maximale Schleudertouren: 800 U/min / Wasserverbrauch: 50 l</p> <p>249,95 €</p> <p>Betriebskosten (bei 9,0 Jahren Nutzung)</p> <p>Gesamtkosten = Preis + <u>geschätzte Betriebskosten</u></p> <p>718,18 € = 249,95 € + 468,23 €</p>	<input type="checkbox"/>
	<p>Privileg Basic 78 1000</p> <p>Fassungsvermögen: 4,5 kg / Maximale Schleudertouren: 1000 U/min / Wasserverbrauch: 56 l</p> <p>299,95 €</p> <p>Betriebskosten (bei 9,0 Jahren Nutzung)</p> <p>Gesamtkosten = Preis + <u>geschätzte Betriebskosten</u></p> <p>841,89 € = 299,95 € + 541,94 €</p>	<input type="checkbox"/>

Figure 20: Supplementary information for the treatment group in round two

QUELLE-Berater / »Waschmaschinen suchen ein Zuhause«

Betriebskosten

Den Kaufpreis zahlen Sie nur einmal; die Betriebskosten fallen dagegen über die gesamte Nutzungsdauer der Waschmaschine an. Was kurzfristig gesehen preiswerter erscheint, kann langfristig teurer sein. Vergleichen Sie die Summe aus Kaufpreis und geschätzten Betriebskosten, um herauszufinden, welches Gerät für Sie am günstigsten ist.

Klicken Sie auf "geschätzte Betriebskosten", um die Betriebskosten-Berechnung an Ihre persönliche Situation anzupassen - hinsichtlich Nutzungsdauer, Nutzungen pro Woche, Strompreis und Wasserpreis.

Figure 21: Detailed product comparison in the online shop's treatment group

QUELLE-Berater/»Waschmaschinen suchen ein Zuhause«




	Miele W 4146 WPS	Privileg Dynamic76606
		
	[Produktdetails anzeigen] [Aus Vergleich entfernen]	[Produktdetails anzeigen] [Aus Vergleich entfernen]
▼ Allgemeine Daten		
Gesamtkosten	1.649,74 €	1.145,37 €
Betriebskosten	<i>i</i> 489,79 €	445,42 €
Preis	<i>i</i> 1.159,95 €	699,95 €
Hersteller	Miele	Privileg
Name	W 4146 WPS	Dynamic76606
Abmessungen	<i>i</i> 85 cm x 59,5 cm x 63,4 cm	85 cm x 60 cm x 60 cm
Besonderheiten	k.A.	k.A.
Garantie	<i>i</i> 36 Monate	24 Monate
Gewicht	<i>i</i> k.A.	k.A.
▼ Technik		
Waschwirkungsklasse	<i>i</i> A	A
Energie-Effizienz-Klasse	<i>i</i> A Plus	A Plus
Schleuderwirkungsklasse	<i>i</i> A	A
Energieverbrauch	<i>i</i> 1,02 kWh	1,02 kWh
Wasserverbrauch	<i>i</i> 47 l	39 l
maximale Schleudertouren	<i>i</i> 1600 U/min	1600 U/min
Fassungsvermögen	<i>i</i> 6 kg	6 kg
Geräuschentwicklung	<i>i</i> k.A.	k.A.
Programmzahl	<i>i</i> 11	k.A.
pro Jahr Energieverbrauch	<i>i</i> 204 kWh	204 kWh
Leistung	<i>i</i> k.A.	k.A.
Technik Zusatzinformation	k.A.	k.A.
▼ Ausstattung		
Energiesparfunktion	<i>i</i> ja	ja
integriertes Display	<i>i</i> ja	ja
Kindersicherung	ja	ja
Ausstattung Zusatzinformation	k.A.	k.A.
► Funktionen		
► Konstruktion		
Produkt hinzufügen:		Alle Produkte entfernen
Alle verfügbaren Produkte nach Name sortiert:		
<input type="text" value="AEG LAVAMAT 5211 1200"/>	<input type="button" value="hinzufügen"/>	
		► Fenster schließen 

Figure 22: Comparison of recommendation with customer's preferences


QUELLE-Berater/»Waschmaschinen suchen ein Zuhause«		
Warum wir Ihnen dieses Produkt empfehlen?	Ideales Produkt	↔ Unser Vorschlag: Privileg 38406
Preis		■■■■■□
Ihre Preisvorstellung		
Preis:	bis 400 €	349,95 €
Eine für alles!		■■■■■□
Unsere Empfehlung für "Eine für alles!"		
Waschwirkungsklasse:	≥ A	A
Energie-Effizienz-Klasse:	≥ A	A Plus
Schleuderkategorie:	≥ B	B
maximale Schleudertouren:	≥ 1400 U/min	1400 U/min
Wollschonung:	empfohlen	Ja
Energiesparfunktion:	empfohlen	Ja
Haushaltsgröße		■■■□□
1-2 Personen		
Fassungsvermögen:	≤ 4,5 kg	6 kg
Beladungserkennung:	empfohlen	Ja
Aufstellungsort		■■□□□
Keller oder Waschküche		
Wasserstopp:	nicht notwendig	Nein
Wasserschutz:	nicht notwendig	Ja
programmierbarer Timer:	empfohlen	Nein
Hersteller		■□□□□
Ihr gewünschter Hersteller		
Hersteller:	Miele	Privileg

Appendix III: feedback evaluation

Figure 23: Feedback form for the treatment group of the online shop

QUELLE-Berater / »Waschmaschinen suchen ein Zuhause«

Ihre Meinung ist uns wichtig!



Wir möchten Sie auch in Zukunft gut beraten. Deshalb legen wir großen Wert auf Ihre Meinung und Ihre Anregungen. Mit Ihrer Hilfe können wir uns weiter verbessern. Herzlichen Dank für Ihre Unterstützung.

Wie gut fühlen Sie sich beraten?
Bitte bewerten Sie uns!

Was ist der Hauptgrund für Ihre Beurteilung?

- die Benutzerführung
- das Beratungsergebnis
- die Betriebskosten-Berechnung
- die Fragestellung
- das Produktsortiment
- der Informationsgehalt

Haben Sie eine passende Waschmaschine gefunden?
Bitte treffen Sie eine Auswahl!

Haben Sie schon einmal eine spezielle Betriebskosten-Webseite besucht?
Nein

Haben Sie sonstige Anregungen oder Vorschläge?

Für welche Produkte wünschen Sie sich außerdem eine Beratung?

- DVD / Home Cinema
- Mobiltelefone
- Drucker
- Netzwerk / Router / Wireless LAN

andere Warengruppe

Ihre E-Mail Adresse (optional) für eventuelle Rückfragen:

Ihre Meinung ist uns wichtig! Sichern Sie sich für kurze Zeit den limitierten 10-Euro-Gutschein! Geben Sie Ihre E-Mail-Adresse an und wir setzen uns mit Ihnen in Verbindung. Wir freuen uns über Ihr Feedback!

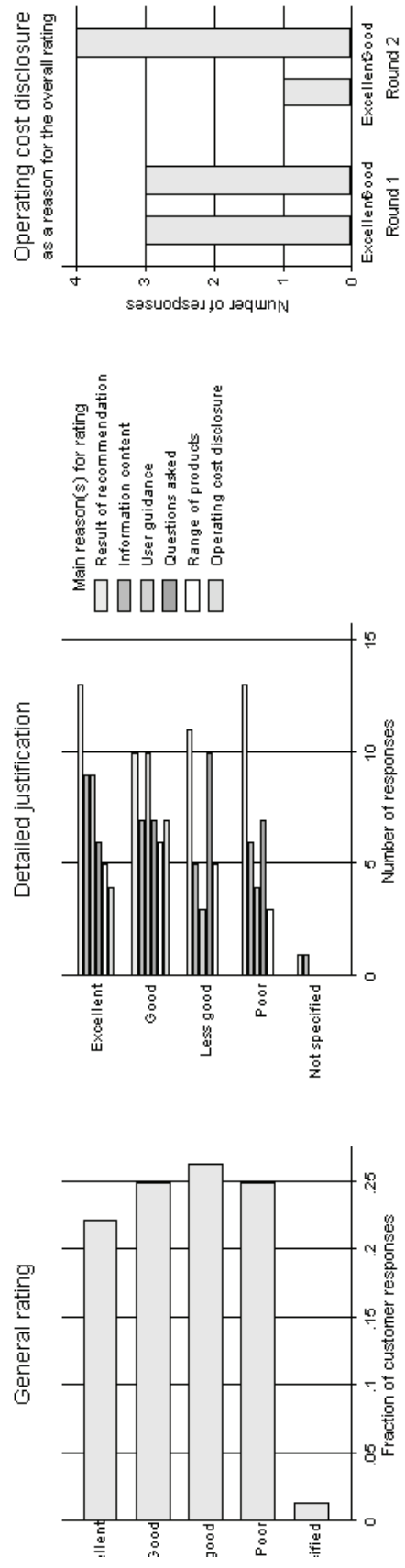
[→ Ihre Meinung absenden](#)

Table 80: Answer options in the pull-down menus of the feedback form

<i>Question</i>	<i>“Wie fühlen Sie Sich beraten?”</i>	<i>“Haben Sie eine passende Waschmaschine gefunden?”</i>	<i>“Haben Sie schon einmal eine spezielle Betriebskosten-Webseite besucht?”</i>
<i>Option</i>			
1	“Sehr gut”	“Ja, und ich habe sie gleich hier gekauft”	“Nein”
2	“Gut”	“Ja, aber ich werde sie anderswo kaufen”	“Ja, www.ecotopten.de ”
3	“Weniger gut”	“Ja, aber ich wollte mich nur informieren”	“Ja, www.energiesparende-geraete.de ”
4	“Schlecht”	“Nein”	“Ja, www.spargerade.de ”
5			“Ja, www.stromeffizienz.de ”
6			“Ja, andere Webseite”

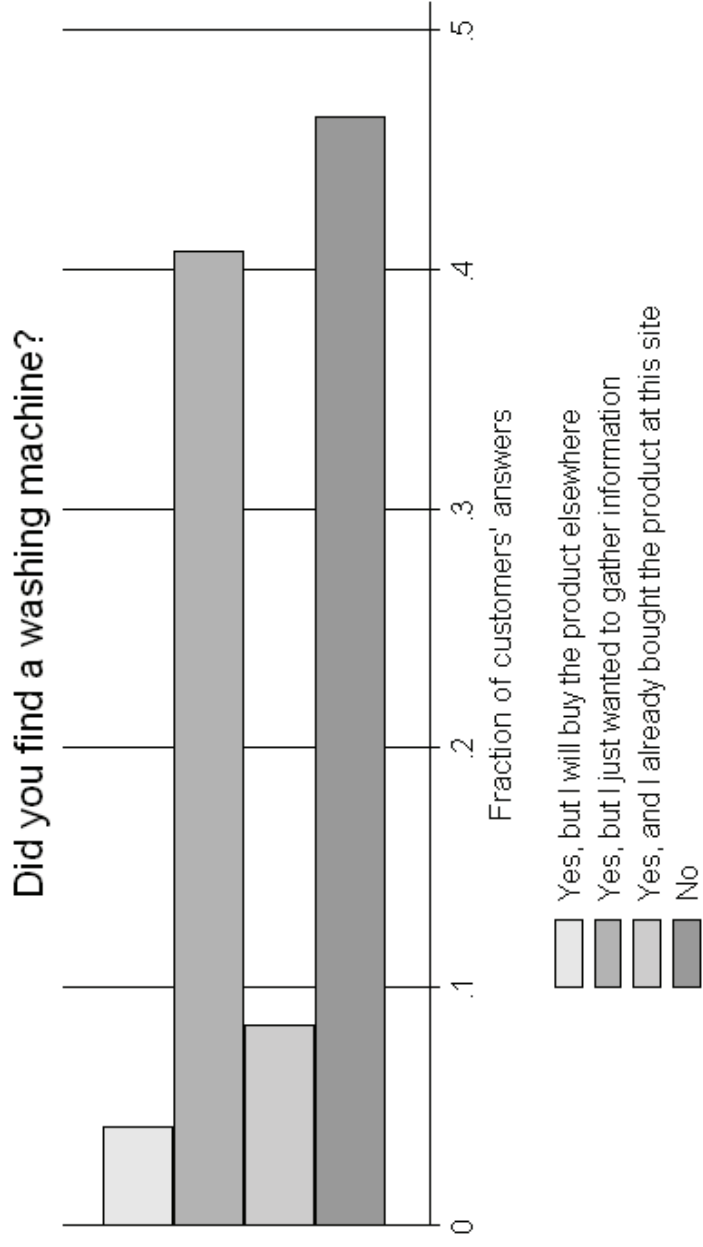
Figure 24: Evaluation of customer satisfaction with the recommendation agent

How do you rate the agent's recommendation?



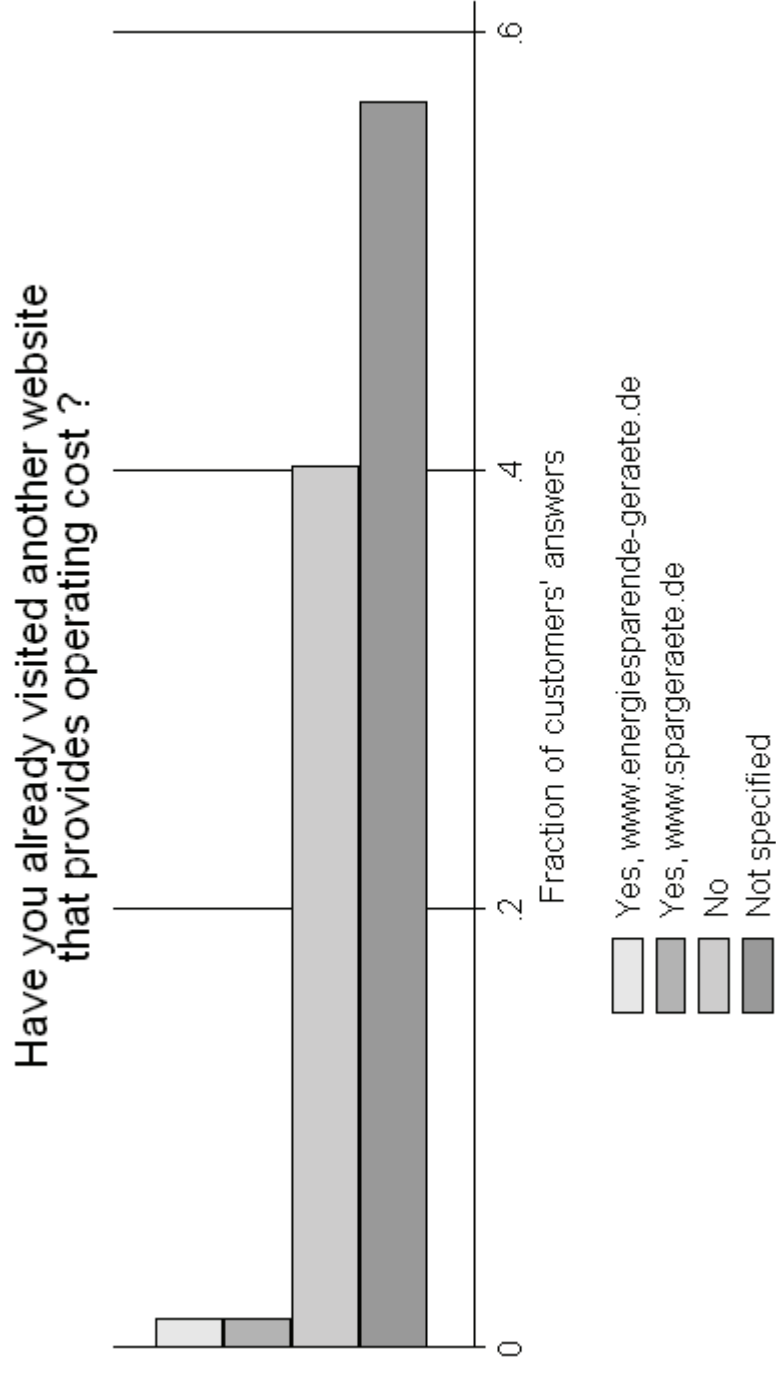
Note: Feedback from 72 customers. Customers could provide more than one reason for their rating. 'Round 1' and 'Round 2' refer to the different experimental treatment rounds.

Figure 25: Evaluation of the recommendation agent's effect



Note: Feedback from 72 customers

Figure 26: Evaluation of the customer's knowledge of other websites



Note: Feedback from 72 customers

Appendix IV: transcribed qualitative interviews

Table 81: Interview participants

<i>Interview No.</i>	1	2	3	4	5	6	7	8
Experimental round	1	1	1	1	1	2	2	2
Recommendation system type	Simple search	Simple search	Simple search	Simple search	Simple search	Simple search	Simple search	Simple search
Age group	40 to 49	20 to 29	30 to 39	60 and older	40 to 49	40 to 49	30 to 39	30 to 39
Sex	Female	Male	Female	Male	Female	Female	Female	Male
Education ^a	“Studium”	“Studium”	“weiterführe nde Schule”	“Haupt- bzw. Volksschule”	“Studium”	“Haupt- bzw. Volksschule”	“weiterführe nde Schule”	“Abitur”
Employment status	Employed	Employed	Employed	Retired	Employed	Employed	Employed	Employed
German State	North Rhine-Westphalia	Hesse	North Rhine-Westphalia	Baden-Württemberg	Brandenburg	Berlin	Lower Saxony	Hesse
Time of first internet use	1991	1994	2004	1995	1997	mid-90s	1997	Early internet user

Note: ^a Given the special structure of the German educational system, these standard answers are not translated into English

Table 82: Interview transcripts

Interview topics

1. The participant's reaction to and understanding of the disclosed operating cost
2. Assumptions that underlie the calculated operating cost, their potential adjustment, and the role of rising energy prices
3. Importance of energy efficiency for the participant
4. Knowledge of alternative information channels regarding energy efficiency of appliances
5. Personal opinion about the value and the future of operating cost disclosure
6. Further comments

Interview No. 1

- 1 Ich war im ersten Moment ein bisschen erstaunt und habe dann erst einmal geguckt, wie sich die Betriebskosten zusammensetzen. Weil das ist ja so dargestellt wie ein Gesamtpreis, hinterher. Und da musste ich erstmal einen Moment gucken, wie sich das zusammensetzt, weil Betriebskosten fallen ja nun bei jeder Waschmaschine an. Da ist es mir im Großen und Ganzen - ich will nicht sagen - egal, weil erstmal nebensächlich, die Betriebskosten. Mich interessiert dann, wenn ich so etwas sehe, erst einmal der Preis der Maschine an sich. Und so, wie das dargestellt ist, das ist ja ziemlich groß und in rot - der Komplettpreis - das fand ich dann in dem Moment erst einmal erstaunlich.
- 2 Das war schon ganz klar. Man kann das ja dann entsprechend unter Betriebskosten anklicken, und das war dann eigentlich schon einsichtig, wie sich das errechnet. Wobei das ja immer nur geschätzte Werte sind. Man geht dann ja immer von einer Standardfamilie aus, und Standard-Wäschen in der Woche und Standard-Wäschen im Jahr, und daraus errechnet man das dann. Ich habe mir das angeguckt, und gesehen: Aha, so setzt sich das zusammen, und habe das dann so gelassen. Weil, wie schon gesagt, mich die Betriebskosten so primär nicht interessiert haben. Mich hat ja erstmal die Maschine und der Preis interessiert. Mir war die Maschine wichtig, weil das ist eine Summe die - selbst, wenn man sie auf Raten kauft - man erst einmal aufbringen muss. Betriebskosten ergeben sich im laufenden Betrieb über das Jahr verteilt. Und mir persönlich ist dann der Preis der Maschine - so wie er dort dargestellt wird - viel wichtiger als die Betriebskosten.
- 3 Ist schon ein wichtiger Punkt für die Entscheidungsfindung: was für eine Energieeffizienz-Klasse ist das, was für eine Wasch-Effizienzklasse, wie viel Wasser verbraucht die Maschine, wie viel kann man laden? Wie freundlich ist die Bedienung? Ist eine große Öffnung da? Also das sind schon Sachen, die wichtig sind.
- 4 -

- 5 Mir reicht diese Klassifizierung schon. Da gibt es auch im Katalog bei Quelle entsprechende Tabellen, da wird ausgeführt, was A, B und C ist. Diese Effizienzklassen gibt es ja auch bei anderen Geräten. Und da reicht mir das eigentlich schon, wenn ich das im groben weiß. Ich muss das nicht unbedingt mathematisch festmachen an einem Betrag, den ich dann errechne. Und ich weiß, wenn das Klasse A hinsichtlich der Energie-Effizienz ist, dann weiß ich auch, dass weniger Energie verbraucht wird als z.B. bei "G". Also das ist mir dann klar, und dann muss ich das auch nicht explizit ausrechnen. Ich denke, da hat jeder seine eigene Meinung. Der eine sieht es so, der andere kann es vielleicht besser an Zahlen festmachen. Ich finde das immer hilfreich, wenn die Möglichkeit zumindest angeboten wird. Wir haben Kühlschränke oder besser gesagt Gefrierschränke gekauft Anfang letzten Jahres und, - da muss man halt suchen. Es sind so viele Sachen im Angebot. So viele Klasseneinteilungen. Man muss dann halt sehen: was bringt das Gerät, was leistet das Gerät, und welche Energie-Effizienz-Klasse ist das letztendlich? Irgendwo muss man das auch ein bisschen in Relation sehen.
- 6 Ich würde die Betriebskosten nicht unbedingt gleich an erster Stelle nennen, sondern ich würde schon vorrangig den Preis der Maschine kennzeichnen. Und dann die Betriebskosten vielleicht daneben - kann ja ruhig gleich groß sein. Vielleicht anstatt in rot in schwarz. Also schon ein bisschen von der Optik her ändern. Also ich finde es nicht schlecht, wenn das auch so ein Berater bei Quelle für andere Geräte angeboten wird. Ich muss sagen, die Maschine, die mir der Berater als erste Wahl angeboten hat, die hätte ich auch genommen, und war dann doch ein bisschen enttäuscht, als ich die bestellen wollte und dann nachher die Meldung kam: "die Maschine ist ausverkauft". Damit war ich nicht so ganz zufrieden, dass die Maschine, die als das Modell angeboten wird, schon ausverkauft ist. Solche Artikel sollte man dann auch rauslassen aus dem Berater. Ich habe die in den Warenkorb gepackt, wollte den abrufen, und da stand "ausverkauft". Im Warenkorb wird auch manchmal ein Alternativartikel angeboten, aber auch das war in diesem Fall nicht möglich. Im Grunde genommen ist dann das ganze im Sande verlaufen.

Interview No. 2

- 1 Ich war überrascht über die Höhe, weil auf den ersten Blick nicht erkennbar war, dass es über die gesamte Nutzungsdauer war. Wenn man darauf geklickt hat, hat man ja gesehen, dass 4,9 Jahre die Grundlage war. Das war neu, weil ich so etwas noch nie gesehen habe und ich mir über die Kosten nicht im Klaren war, aber das war dann in Ordnung sozusagen.
- 2 Das war alles klar, ich musste es nur noch einmal anpassen - die Anzahl der Maschinen pro Woche. Nein, ich kenne meinen genauen Strompreis nicht; ich kenne auch nicht die Wasserkosten. Wobei der Strompreis, der da erschien, schien in Ordnung zu sein. Ich fand die Unterschiede bei den einzelnen Maschinen nicht so extrem. Ich hatte gedacht, dass die Unterschiede größer sind. Aber wenn man das über 5 Jahre rechnet, ist es nicht so, dass es sich lohnt, dafür 100 Euro mehr auszugeben für die Waschmaschine. [Den Zeithorizont anzupassen], habe ich nicht überlegt.
- 3 Ich gucke immer, dass es im A oder B ist, ohne, dass ich mir bewusst bin über die Konsequenzen davon. Ich vergleiche dann eher Maschinen untereinander nach den Kriterien. Das sind ja bei der Waschmaschine drei oder zwei. Ich komme da durcheinander mit den Spülmaschinen. Energie, Waschleistung, Schleuderleistung. Da vergleiche ich die Maschinen untereinander.

- 4 Darauf schaue ich auch im Laden immer bei allen Produkten. [Andere Internetseiten kenne ich] nicht für Elektrogeräte. Ich habe mal meinen Stromverbrauch kontrollieren lassen. Die Seite weiß ich aber nicht mehr. Und das passte ziemlich genau. Das war ein ganz gutes Ergebnis.
- 5 Ich finde das ist eine interessante Information. Dieses Thema wird auch an Bedeutung gewinnen. Das ist auch sinnvoll bei Computer, Fernseher (was den ganzen Tag läuft). Wenn man sich da bewusst wäre über die jährlichen Kosten - das würde das Bewusstsein erhöhen
- 6 Das Layout war in Ordnung und angemessen. Man kauft sich ja ein Gesamtpaket. Das könnte man sich noch einmal jährlich darstellen. Vielleicht eine Notiz, warum 4,9 Jahre angekommen werden für die Lebensdauer. Mein Problem: die Tür in der Küche ist 50cm breit und die Waschmaschine muss dadurch passen. Ich konnte das nicht direkt mit einer Anfrage lösen, weil man nur entweder Breite oder Tiefe angeben kann. Und entweder Frontlader oder Toplader entscheiden konnte. Das hat mein Problem nicht gelöst.

Interview No. 3

- 1 Das fand ich super. Das fand ich absolut spitze. Das war für mich neu. Das war sofort klar. Das war schön übersichtlich, und finde ich auch gut, dass man das dann vergleichen kann.
- 2 Da habe ich nicht näher nachgesehen. Was ja da stand, war 4-Personen-Haushalt. Ich denke mal, das sind Durchschnittswerte, wie oft da Waschmaschinen genutzt werden. Ich denke, das sind für alle gleiche Maschinenladungen. Und dann variieren am Ende nur die Zahlen, je nachdem, wieviel Stromverbrauch und Wasserverbrauch eine Maschine hat. Die [Energiepreise] gehen ja leider nach oben. Energiekosten sind für mich auch wichtig.
- 3 Da habe ich immer drauf geachtet, dass - wenn ich mir etwas Neues zulege - das Maschinen sind, die einen niedrigen Wasserverbrauch und Stromverbrauch haben.
- 4 [Eine solche Internetseite sehe ich] zum ersten Mal.
- 5 Ich denke, das ist schwierig. Für Spülmaschinen wäre es noch interessant. Und Kühlgeräte. Für Herde wäre das ja schwierig.
- 6 Ich hätte es schön gefunden, wenn auch noch spezielle Programme angeboten würden. Wenn ich Wasche - ich habe einen großen Haushalt, und ich mache oft das Kurzprogramm. Und das war nun überhaupt nicht ersichtlich. Das war für mich wichtig, und da musste ich mich nun trotzdem wieder durchwurschteln. Also dass man da ein paar Möglichkeiten mehr hätte, herauszufinden, was die geeignete Waschmaschine ist. Und was ich schade fand: zum Beispiel hatte ich Privileg angeklickt als Marke und trotzdem wurde mir Miele und alles auch mit angezeigt. Da habe ich gedacht, das ist ja doof. Es war Privileg dabei, aber eben auch Privileg.

Interview No. 4

- 1 Ja gut, ich habe erst die Gesamtkosten angeguckt und gedacht: "Mensch, das ist weniger!" Und dann habe ich gesehen: "hoppla, das sind die Betriebskosten". Das habe ich nicht unbedingt erwartet. [Die Betriebskosten waren aber] ohne weiteres nachvollziehbar.

- 2 Ich habe gedacht, dass das schon stimmt. Habe nirgendwo draufgeklickt. Bei Quelle, habe ich gedacht, da stimmt das schon. Wenn ich es woanders gemacht hätte, dann hätte ich dem nicht so getraut. Soweit [an steigende Energiepreise] habe ich nicht gedacht. Das hat keine Rolle mehr gespielt. Wenn man die Maschine hat, dann ist es ja vorbei. Soweit ging's nicht.
- 3 [Das ist] schon wichtig. Ich habe schon geschaut, dass ich eine sparsame Maschine nehme, wobei ich gleichzeitig drauf geschaut habe, die mit dem allergeringsten Wasserverbrauch wollte ich nicht, weil ich dem nicht getraut habe. Nicht die mit dem allergeringsten Verbrauch habe ich dann genommen, aber die nächste Stufe. Aber die mit viel Verbrauch hätte ich natürlich nicht genommen. Wasser ist ja auch gleichzeitig Strom.
- 4 [Auf Energieeffizienz habe ich] schon irgendwie drauf geachtet, aber heute schon mehr. Das habe ich sonst noch nicht [auf anderen Internetseite] gesehen.
- 5 Man kennt es ja von Kühlschränken her, da macht das schon Sinn. Der ist ja im Dauerbetrieb. Ohne Dauerbetrieb ist das vielleicht zweitrangig.
- 6 Ich habe gedacht, so kann es nicht gedacht sein. Ich wusste im Prinzip schon, welche Maschine ich wollte, die im Test gut abgeschnitten hat. Ich habe den normalen Berater benutzt. Da konnte ich eingeben, was ich wollte, es ist alles gekommen, nur diese Maschine nicht. Und dann habe ich gedacht, dass kann eigentlich nicht gewollt sein. Später bin ich noch in die Profiberatung gegangen und habe die irgendwie raus gebracht. Ich habe es mit allem ausprobiert, aber die Maschine war nicht drin. Aus meiner Sicht macht die Trennung zwischen Profi- und Normalberatung nicht viel Sinn. Das ist mein Gedanke.

Interview No. 5

- 1 Die Anzeige ist für mich eigentlich selbstverständlich. Ehrlich gesagt habe ich es mir nicht ganz genau angeguckt, deswegen kann ich dazu eigentlich nicht viel sagen.
- 2 Die Änderung von Energiepreisen kommt mir bei anderen Gelegenheiten eigentlich mehr. Hierbei eigentlich nicht.
- 3 Ja, aber da gibt es einige Dinge, die mir nicht gefallen. Es wird ja viel auch über Wasserersparnis gesprochen was die Waschmaschinen betrifft. Ich habe eine Waschmaschine, die wenig Wasser verbraucht, aber die Wäsche wird nicht sauber und das gefällt mir überhaupt nicht. Da ist mir zu wenig Wasser drin, dadurch wird das Waschpulver überhaupt nicht verteilt. Da habe ich schlechte Erfahrung. Also wenig Wasser ist für mich bei einer Waschmaschine überhaupt nicht wichtig. Die Energie ja, aber nicht das Wasser.
- 4 Habe ich immer nur bei Quelle gemacht.
- 5 Bei Geschirrspülern macht man das doch schon, oder? Bei Fernsehern muss es nicht unbedingt sein. Bei Kühlgeräten auch. Das ist wichtig.
- 6 Ich fand die Waschmaschinen-Suche sehr unübersichtlich. Für einen 1-Personen-Haushalt ist das nicht so richtig deutlich geworden. Danach wurde nicht richtig gefragt bei der Haushaltsgröße. 1-2 Personen reicht mir nicht. Es ist eine, nicht zwei. Das ist schon sehr viel.

Interview No. 6

- 1 Kann ich jetzt nicht sagen. Helfen Sie mir auf die Sprünge. Welche Parameter sieht man da als erstes? Danach habe ich gar nicht geguckt. Ich habe auf Stromverbrauch und Wasserverbrauch geachtet. Und das ist ja alles besser, als was ich bis dato hatte. Die Betriebskosten helfen mir echt nichts, denn da kann ich nicht dran drehen. Ich gucke auf den Wasserverbrauch, und der ist super. Und der Stromverbrauch ist auch besser als bisher. Und was die tatsächliche Umrechnung in Kosten angeht - das ist nachher Sache des Energieversorgers und der Wasserwirtschaft, die ja ihre Preise unabhängig davon gestalten, wie viel oder wie wenig ich verbrauche. Mir reichen die Zahlen so - bei Strom in kWh, bei Wasser in Liter. Und das sind meine Vergleichsparameter. Die sind schon immer sehr gut.
- 2 [Sind steigende Energiepreise wichtig?] Ja klar, aber das sind wie gesagt Parameter, die ich nicht ändern kann.
- 3 [Effizienz war wichtig-] die letzten 15-20 Jahre doch schon.
- 4 Ich informiere mich über die Info-Materialien im Fachhandel. [Das] kommt immer dann, wenn etwas kaputt geht. Das letzte mal bei Kühlschränken. Wir haben auf etlichen Internetseiten geguckt. Bei Bewag oder Geräteherstellern, aber konkret kann ich keine Angaben mehr machen.
- 5 Die Preise ändern sich ja jährlich. Deshalb hilft es mir nicht, wenn unter dem Strich steht: " Sie verbrauchen - was stand da: für einen Vier-Personen-Haushalt - 194 €. Hilft mir nichts die Zahl, weil der Stromverbrauch regional sehr unterschiedlich ist. Privat gucke ich bei anderen Geräten nach dem Verbrauch in kWh. Das ist eine Größe, die über die Jahre ja konstant bleibt. Die Einheit bleibt konstant. Beim Preis gibt es ja jährlich oder ein zweimal Preiserhöhungen, so dass ich das letzten Endes nicht beeinflussen kann. Von daher ist für mich wichtig zu sehen: okay, so eine Waschmaschine braucht so und soviel Liter Wasser. Und demzufolge so viel Strom. Für andere Leute kann das sehr sinnvoll sein. Manch einer sagt vielleicht: "ich habe über das Jahr so und soviel Euro und das muss über das Jahr reichen". Das sind vielleicht andere Gesichtspunkte, so dass das andere sehr betrifft.
- 6 Wir haben einen Wäschetrockner gesucht, und über die Menüführung wurde mir die Frage nicht angeboten. Es gab nur Waschmaschine oder Trockner.

Interview No. 7

- 1 [An die Reaktion] kann ich mich nicht mehr erinnern. Das hat mich in dem Moment noch gar nicht so interessiert, eigentlich.
- 2 Das hat mich gar nicht weiter interessiert, weil mich ja erstmal eine Maschine interessiert. Es gibt tausend Maschinen mit tausend Betriebsarten, und ich habe mich noch nicht einmal für eine entschieden. Von daher hat mich das zu dem Zeitpunkt nicht interessiert. [Steigende Energiepreise sind] bei einer Waschmaschine nicht so wichtig, weil wir da nicht die Mengen haben. Das gleiche gilt für Wasser.
- 3 Darüber habe ich mich vorher schon informiert, über die einzelnen Effizienz-Klassen: E, etc. damit habe ich mich vorher schon auseinander gesetzt.
- 4 [Ich habe mich] im Internet informiert. Aber an bestimmte Seiten erinnere ich mich nicht mehr.

- 5 Die Betriebskostenanzeige ist einfach zu früh. Wenn ich mich für eine Maschine interessiere - ich habe ja auf anderen Seiten noch weiter geguckt - dann interessiert mich das schon ein bisschen. Aber ich möchte erst einmal die passende Maschine haben, weil ich kann nicht mit Energieeffizienz an den Markt gehen - von meiner Seite aus - und ganz zum Schluss habe ich eine 3-Kilo-Maschine, womit ich nichts anfangen kann. Für mich ist das das letzte, worauf ich - das ist noch ein Entscheidungskriterium zum Schluss, aber nicht das erste Entscheidungskriterium. Wo ich das zum Beispiel interessanter finden würde, wäre bei Gefriergeräten. Weil da das Gerät das ganze Jahr läuft. Wie gesagt, meine Waschmaschine läuft dreimal in der Woche. Da brauche ich mich nicht großartig drum zu kümmern.
- 6 Mich hat die Seite weder angesprochen, noch hat sie ihren Zweck erfüllt. Da kann ich bei Ebay eine größere Auswahl treffen.

Interview No. 8

- 1 Ja, war mir ziemlich klar. Ich habe das Gerät deswegen auch ausgewählt, weil ich mir schon vorher mit der Stiftung Warentest Gedanken darüber gemacht habe, was eine Maschine im Jahr verbraucht. Das war das schon ungefähr - damit habe ich gerechnet. Das war für mich der entscheidende Kaufgrund. Zuerst haben wir nicht verstanden, dass wir unsere eigenen Daten eingeben mussten für Energiepreis und Wasserpreis. Ich habe das mit meiner Frau zusammen gemacht. Beim zweiten Mal haben wir dann gesehen: Halt - unsere Daten müssen eingegeben werden, damit es die richtigen Daten auswirft.
- 2 Das war in Ordnung. Ich denke mal, dass das Durchschnittswerte von der Bundesrepublik Deutschland sind, wobei die für uns nicht relevant waren. Strompreis war in Ordnung, Wasserpreis war - den hätte ich gerne, den Wasserpreis. Sie meinen den Wasser- und Strompreis in den nächsten 10 Jahren? [genau] Da mache ich mir aus einem Grund Gedanken, aber nicht aus dem, den Sie sich vielleicht denken. Wir haben einen landwirtschaftlichen Betrieb mit eigenem Brunnen, und ich habe mir darüber Gedanken gemacht, ob ich vielleicht das Wasser für die Waschmaschine aus dem Brunnen herausnehmen soll. Die Waschmaschine ist drei Tage vorher kaputt gegangen. Ich habe sie auseinander genommen, habe reingeschaut, habe gesagt: "Das geht nicht mehr." Und dann war die Frage, wo gucken wir - übrigens ist das bei allen Elektrogeräten so - nicht nur auf den Anschaffungspreis, sondern auch auf die Verbrauchskosten im Lauf der Jahre... wir sind von 10 Jahren ausgegangen. Das Programm hat aber glaube ich nur 9 Jahre angezeigt. Das ist ein bisschen kurz für eine Waschmaschine. 10 Jahre sollte die mindestens laufen - mindestens! Als Anregung noch: die Nutzungsdauer ist zu kurz gewesen, meines Erachtens. Für mich sollte eine Maschine 10, 12 Jahre eigentlich laufen.
- 3 -
- 4 Ich habe gehört, dass es andere Effizienz-Internetseiten geben soll, das habe ich aber erst im Nachhinein gehört. Irgendwo habe ich das gelesen. Da gibt es eine "Sparsseite" oder so etwas. Habe ich irgendwo gehört oder gelesen. Die waren mir aber vorher überhaupt nicht bekannt. Bei EON-Mitte habe ich nachgeguckt, glaube ich.

- 5 Das kommt auf die Geräte an. Beim Toaster nicht, beim Fernseher könnte ich mir das schon vorstellen, wobei der ja auch nicht so viel verbraucht. Energiesparlampen bzw. normale Lampen würden mich interessieren. Kühlschrank ist sehr interessant, Gefriertruhe, Trockner auch. Alles was kühlt oder wärmt, das wäre das.
- 6 Mir ist nicht klar gewesen, dass meine Anfrage nicht an Quelle, sondern an einen Dritten geht. Ich dachte, das geht bei Quelle an irgendeinen Kundenberater oder Sachbearbeiter, der Waschmaschinen verkauft. Da müsste eine Möglichkeit sein, spezielle Fragen zu stellen. Dann fällt mir noch etwas anderes ein: wir haben zuerst eine Waschmaschine gefunden, dann bin ich dazugekommen. Wir haben das System ausgemacht und nach einer halben Stunde wieder hochgefahren. Und dann haben wir die Waschmaschine nicht mehr gefunden - es hat eine Viertelstunde gedauert, bis wir die Waschmaschine wieder gefunden hatten. Das ist vielleicht eher eine Quelle-Angelegenheit mit der Wiederauffindbarkeit.

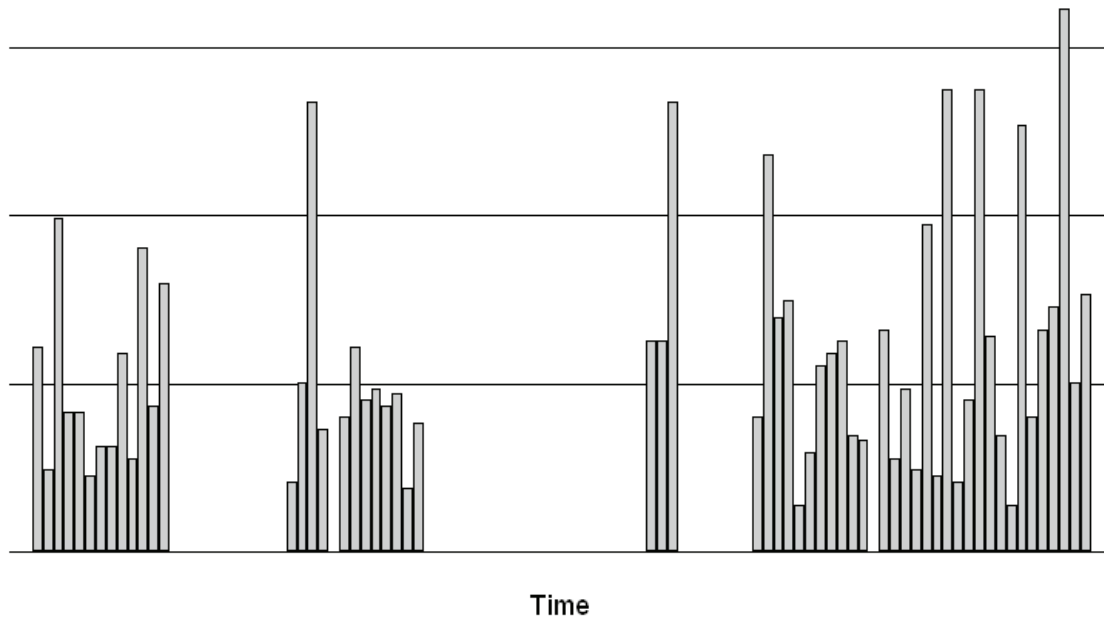
Appendix V: shopbot experiment round 1

Table 83: Server log data for sample user in treatment group (shopbot round 1)

<i>Line</i>	<i>Time</i>	<i>Treat- ment</i>	<i>Event</i>	<i>Click- through in sample?</i>	<i>Merchant number</i>	<i>Product number</i>	<i>Price [Euro]</i>	<i>Energy use [kWh/ year]</i>	<i>Ca- pacity [L]</i>
1	02:54:47	yes	view	no	5	68	1130	306.6	323
2	02:54:47	yes	view	no	19	1442	379.9	500	480
3	02:54:47	yes	view	no	16	70	1329	313.9	315
4	02:54:47	yes	view	no	13	73	2419	460	422
5	02:54:47	yes	view	no	1	105	569	273.8	310
6	02:54:47	yes	view	no	5	121	418	266.5	195
7	02:55:07	yes	click on image	no	19	1442	379.9	500	480
8	02:55:35	yes	click on name	yes	19	1442	379.9	500	480
9	02:56:01	yes	view	no	5	738	536	336	311
10	02:56:01	yes	view	no	16	125	409	233.6	237
11	02:56:01	yes	view	no	5	76	1330	306.6	323
12	02:56:01	yes	view	no	25	94	706.99	350.4	273
13	02:56:01	yes	view	no	10	114	399	306.6	273
14	02:56:01	yes	view	no	13	883	399	329	283
15	02:56:01	yes	view	no	1	127	639	277.4	318
16	02:56:01	yes	view	no	13	71	1549	313.9	311
17	02:56:01	yes	view	no	5	1508	720	358	318
18	02:56:01	yes	view	no	5	1485	489	241	277
19	02:56:25	yes	click on image	yes	5	1508	720	358	318

Note: The click-through in line 7 was not included in the sample for further analysis because it referred to exactly the same product and the same merchant as the one in line 8.

Figure 27: Click-throughs over time (shopbot round 1)



Due to proprietary information concerns, more detailed data cannot be disclosed here.

Table 84: Randomization check for users and clicks (shopbot round 1)

	(1)	(2)	<i>Treatment</i>	(4)	(5)
	All users	All clicks	(3) Freezers	Fridge-f.	Fridges
linux	-0.282* (0.117)	-0.458** (0.142)	-0.503* (0.254)		-0.402* (0.179)
mac	-0.0542 (0.0802)	-0.0146 (0.123)	-0.643 (0.530)	-0.687 (0.513)	0.150 (0.135)
msie55	-0.000834 (0.0822)	0.103 (0.0906)	-0.227 (0.238)	0.0625 (0.278)	0.254* (0.110)
msie60	-0.0650 (0.0390)	0.00394 (0.0659)	-0.212 (0.193)	-0.152 (0.127)	0.109 (0.0839)
firefox10	-0.0499 (0.0502)	-0.0257 (0.0753)	-0.00988 (0.211)	-0.217 (0.143)	0.0157 (0.0981)
firefox15	-0.0817 (0.0439)	-0.0382 (0.0697)	-0.0570 (0.211)	-0.304* (0.133)	0.0900 (0.0886)
netscape	-0.138 (0.130)	0.0585 (0.137)	-0.643 (0.398)		0.254 (0.152)
opera	-0.0676 (0.0666)	0.00754 (0.0930)	-0.176 (0.228)	-0.187 (0.176)	0.133 (0.132)
google	0.0111 (0.0203)				
referrerDE	-0.0127 (0.0280)				
referrerAT	-0.0649 (0.125)				
referrerCH	-0.295* (0.141)				
Prob > F	0.236	0.034	0.080	0.054	0.033
adj. R-sq	0.001	0.004	0.020	0.011	0.008
N	2910	1969	314	581	1074

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Models 3 to 5 include click-throughs to the respective appliance categories. The four last coefficients in model 1 refer to search paths through which users initially arrived at the experimental website.

Table 85: Cookie acceptance (shopbot round 1)

<i>Cookie type</i>	<i>Control</i>	<i>Treatment</i>	<i>Total</i>
<i>All users</i>			
Persistent %	96.8	96.8	96.8
Temporary %	3.2	3.2	3.2
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0013 Pr = 0.971			
<i>Freezers</i>			
Persistent %	99.1	99.1	99.1
Temporary %	0.9	0.9	0.9
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0002 Pr = 0.989			
<i>Fridge-freezers</i>			
Persistent %	97.0	96.6	96.8
Temporary %	3.0	3.4	3.2
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0613 Pr = 0.804			
<i>Refrigerators</i>			
Persistent %	96.3	96.7	96.5
Temporary %	3.7	3.3	3.5
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.1676 Pr = 0.682			

Table 86: Variety in products, brands, and final retailers shown (shopbot round 1)

<i>Cooling appliance category</i>	<i>Number of different products shown</i>	<i>Number of different brands shown</i>	<i>Number of different final retailers shown</i>
<i>Freezers (Overall)</i>			
Control	320	25	34
Treatment	306	25	35
<i>Fridge-freezers (Overall)</i>			
Control	611	33	35
Treatment	611	32	36
<i>Refrigerators (Overall)</i>			
Control	781	30	36
Treatment	774	32	37

Figure 28: Prices and life-cycle costs of all freezers shown (shopbot round 1)

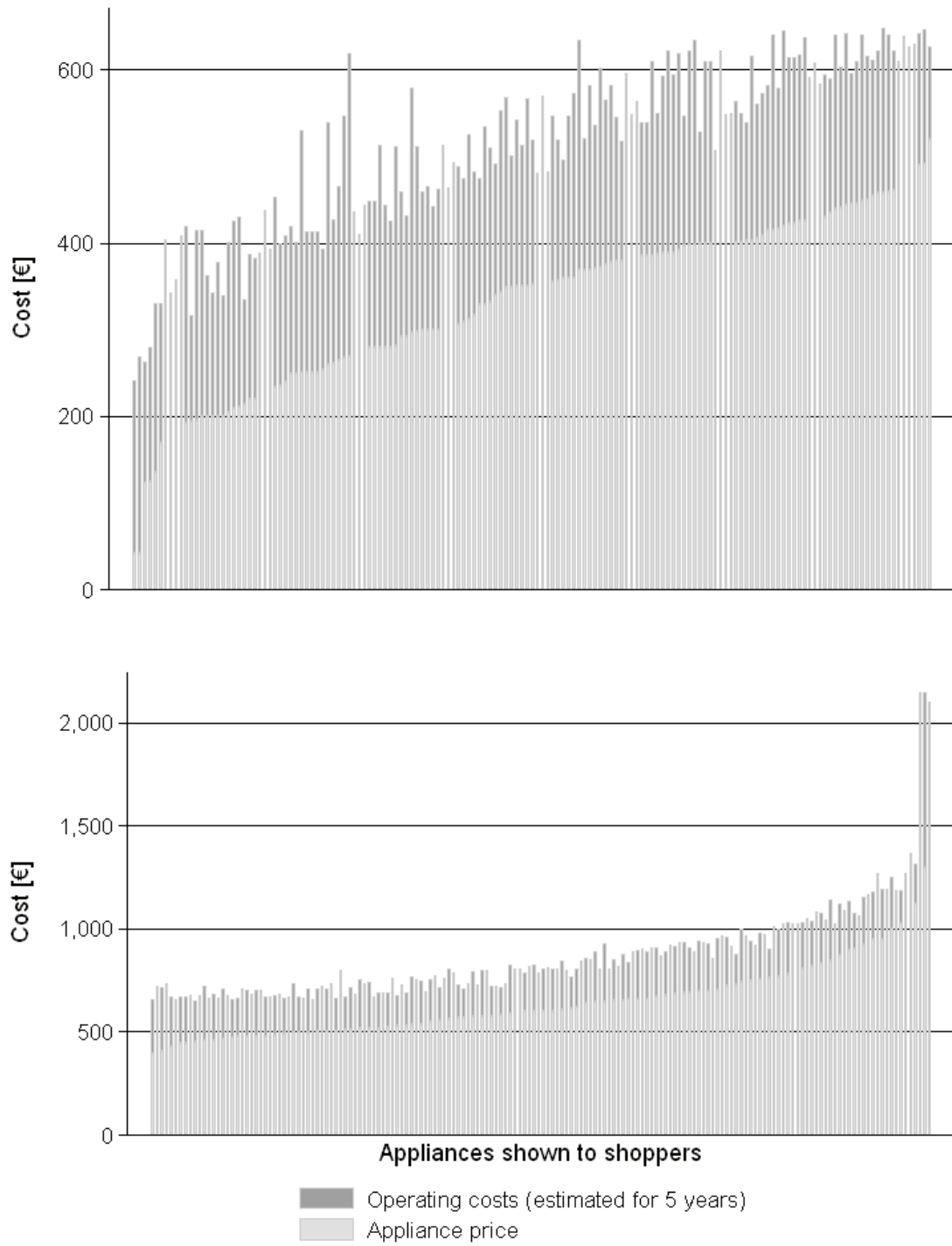
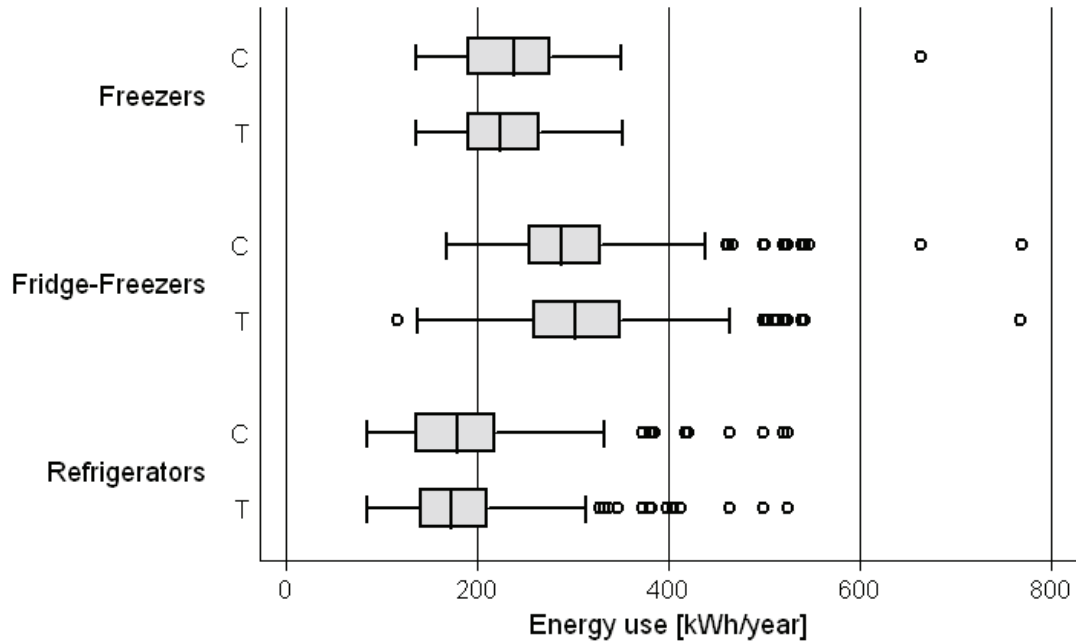


Table 87: Total number of click-throughs per user (shopbot round 1)

<i>Total number of click-throughs</i>	<i>Number of users (Control)</i>	<i>Number of users (Treatment)</i>	<i>Total</i>
1	263	279	542
2	98	98	196
3	56	43	99
4	35	19	54
5	12	11	23
6	8	6	14
7	7	2	9
8	5	2	7
9	7	3	10
10	1	2	3
11	6	5	11
12	1	3	4
13	2	3	5
14	1	0	1
15	0	1	1
16	1	0	1
18	0	1	1
20	0	1	1
22	1	0	1
27	1	0	1
28	0	1	1
35	0	1	1
38	0	1	1
50	0	1	1
Total	505	483	988

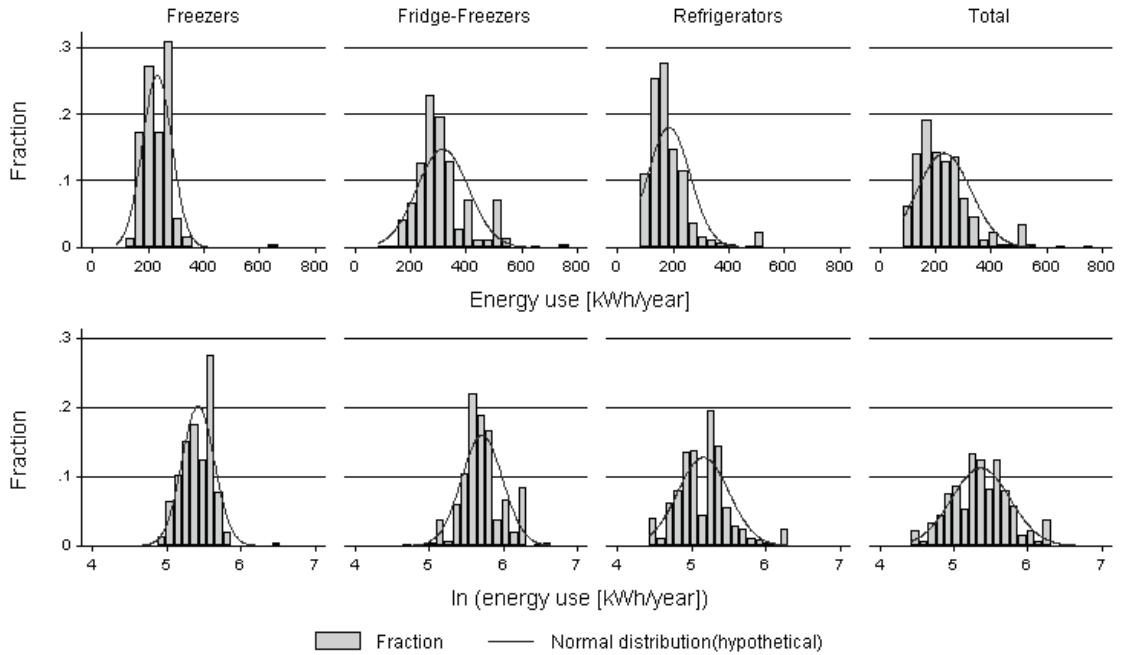
Note: Users with more than 20 click-throughs were not included in subsequent analyses.

Figure 29: Energy use box plots for clicked appliances (shopbot round 1)



Note: N(total)=1969; C-Control; T-Treatment

Figure 30: Energy use histograms for clicked appliances (shopbot round 1)



N(total)=1969

Figure 31: Energy efficiency classes by appliance types (shopbot round 1)

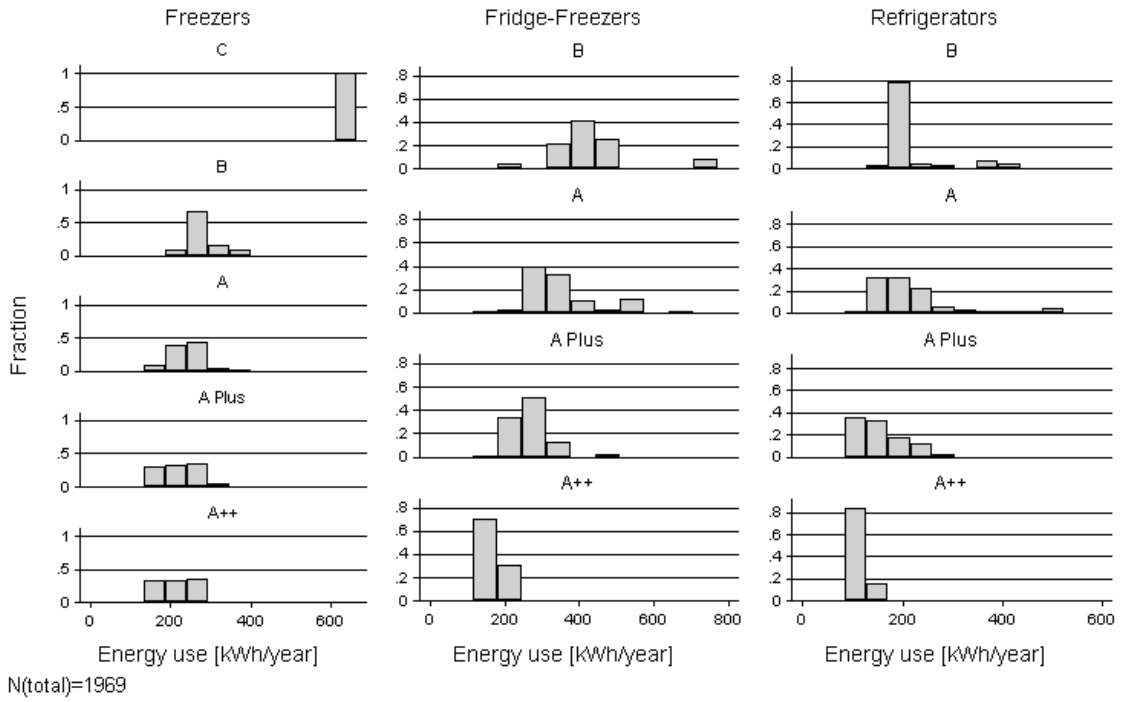


Figure 32: Life-cycle cost histograms for clicked appliances (shopbot round 1)

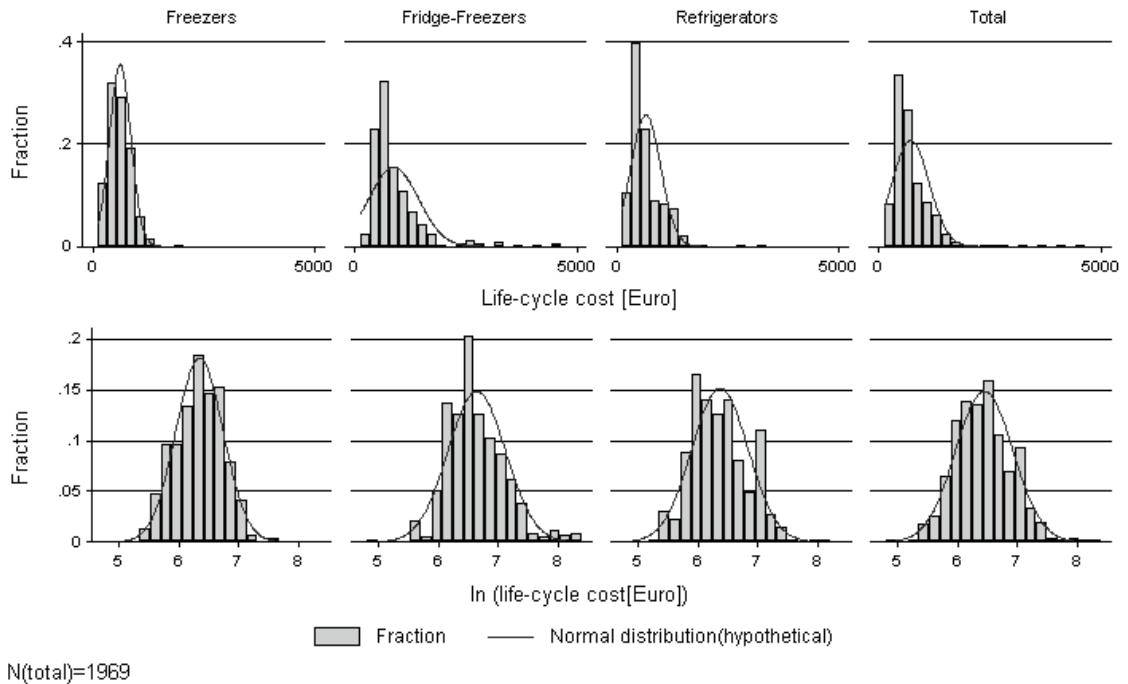


Table 88: Price quartiles for clicked appliances (shopbot round 1)

	<i>N</i>	<i>Min.</i> price	<i>p25%</i> price	<i>p50%</i> price	<i>p75%</i> price	<i>Max.</i> price
<i>Freezers</i>						
Control	170	42	253	399	550	1329
Treatment	144	42	277	392	595	1119
Total	314	42	275	398	569	1329
<i>Fridge-freezers</i>						
Control	288	30	332	475	808	4019
Treatment	293	30	348	465	752	4019
Total	581	30	344	470	799	4019
<i>Refrigerators</i>						
Control	594	109	244	409	609	2419
Treatment	480	105	298	449	693	2788
Total	1074	105	270	429	649	2788
<i>Overall</i>						
Control	1052	30	269	429	635	4019
Treatment	917	30	300	449	685	4019
Total	1969	30	285	441	659	4019

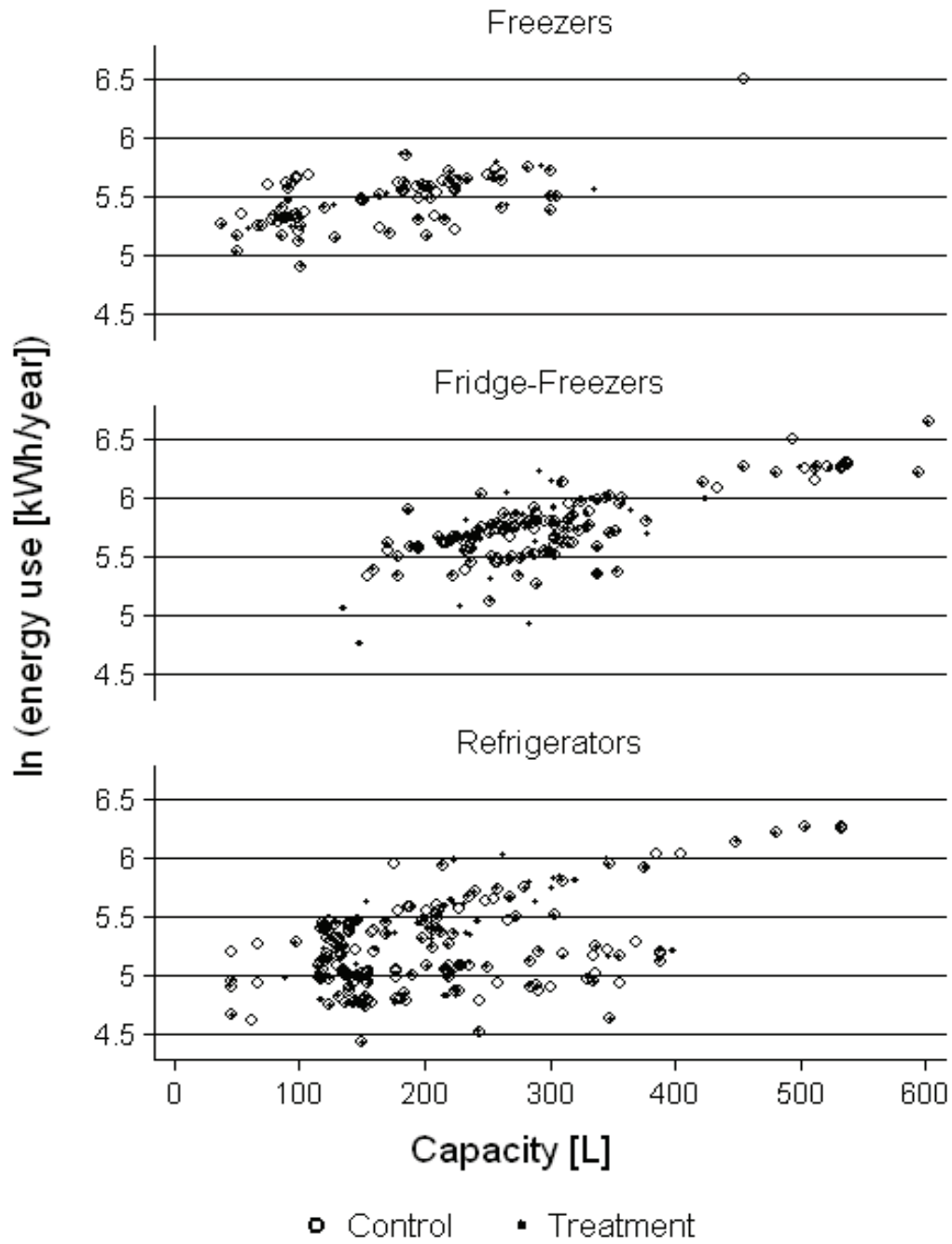
Note: Prices in [Euro]

Table 89: Capacity quartiles for clicked appliances (shopbot round 1)

	<i>N</i>	<i>Min.</i> capacity	<i>p25%</i> capacity	<i>p50%</i> capacity	<i>p75%</i> capacity	<i>Max.</i> capacity
<i>Freezers</i>						
Control	170	38	94	176	208	454
Treatment	144	38	94	167	211	335
Total	314	38	94	171	208	454
<i>Fridge-freezers</i>						
Control	288	154	240	267	315	602
Treatment	293	135	242	283	319	602
Total	581	135	240	277	315	602
<i>Refrigerators</i>						
Control	594	45	131	152	290	532
Treatment	480	45	137	197	291	532
Total	1074	45	135	156	291	532
<i>Overall</i>						
Control	1052	38	137	202	291	602
Treatment	917	38	150	225	291	602
Total	1969	38	140	219	291	602

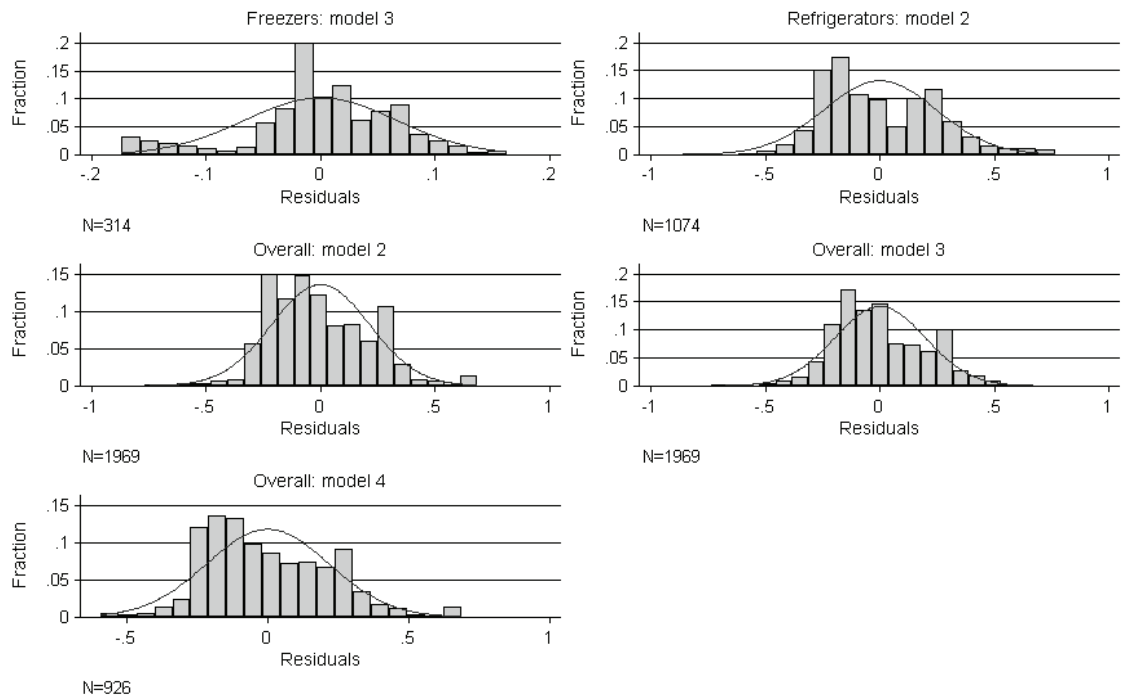
Note: Capacity in [L].

Figure 33: Energy vs. capacity scatter plots for appliances (shopbot round 1)



N(total)=1969

Figure 34: Residuals of selected models (shopbot round 1)



Note: Residuals of models with significant treatment coefficients.

Table 90: Effect size index f^2 for linear regression models (shopbot round 1)

<i>Mode</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>	<i>Model 6</i>
Freezers			0.020			
Fridge-freezers						
Refrigerators		0.0068				
Overall		0.0035	0.0021	0.0051		

Note: Effect sizes only from those models with significant ($p < 0.05$) treatment coefficient(s).

$$f^2 = (R^2_{\text{treatment variables}} - R^2_{\text{no treatment variables}}) / (1 - R^2_{\text{treatment variables}}). \text{ (Cohen 1977, 410-413)}$$

Table 91: Assumed time horizon in the treatment group (shopbot round 1)

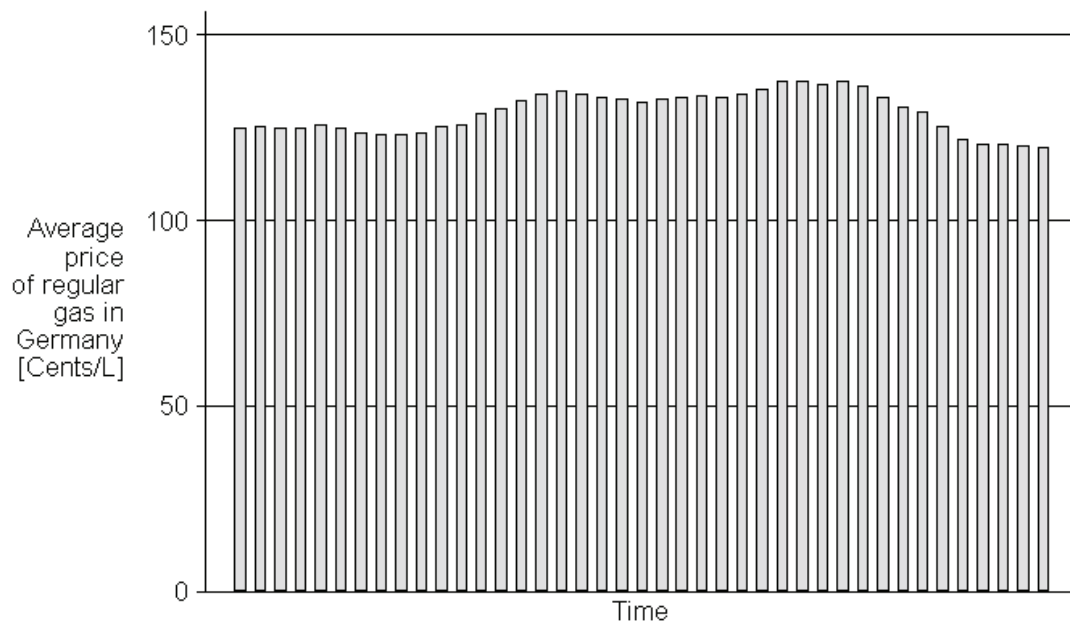
<i>Assumed time horizon [years]</i>	<i>No adjustment</i> (No. of users)	<i>Adjustment, no click-through</i> (No. of users)	<i>Adjustment and click-through(s)</i> (No. of users)	<i>Total</i>	
1	0	29	3	32	2.1%
5*	1458	0	0	1458	97.7%
10	0	0	2	2	0.1%
Total	1458	29	5	1492	100.0%

Note: *default

Table 92: Sorting by life-cycle cost in the treatment group (shopbot round 1)

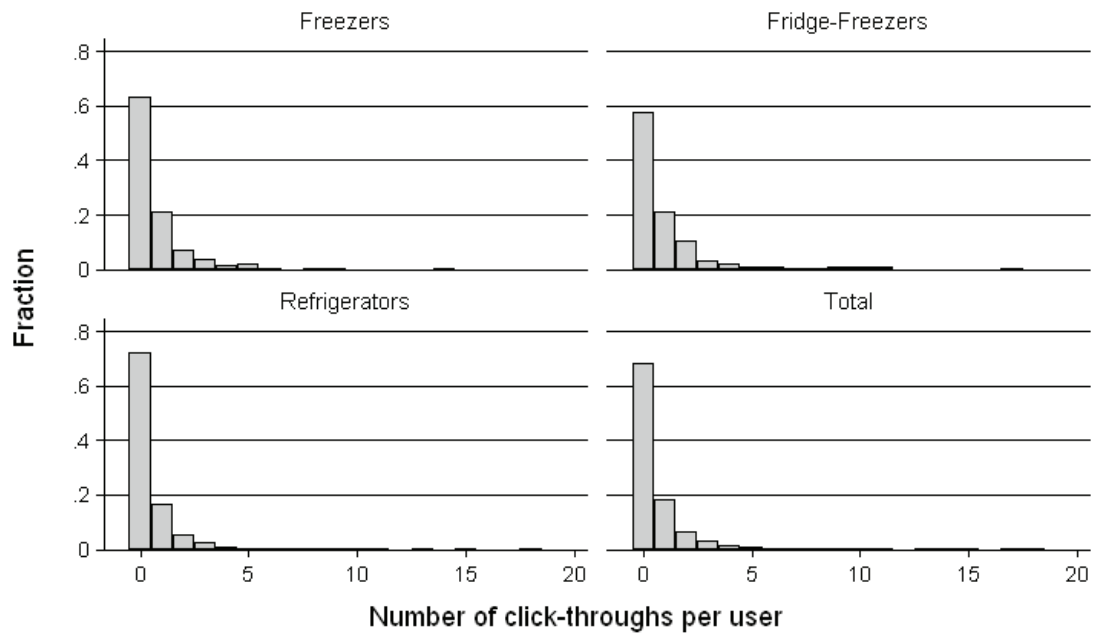
<i>Function with respect to life-cycle cost</i>	<i>Function off</i> (No. of users)	<i>Function on, no click-through</i> (No. of users)	<i>Function on, click-through(s)</i> (No. of users)	<i>Total</i>
Sorting	1486	3	3	1492
Filtering	1492	0	0	1492

Figure 35: Price of gas during the entire experimental timespan (rounds 1 & 2)



Due to proprietary information concerns, more detailed data cannot be disclosed here.

Figure 36: Number of click-throughs per user (shopbot round 1)



N(all click-throughs)=1969

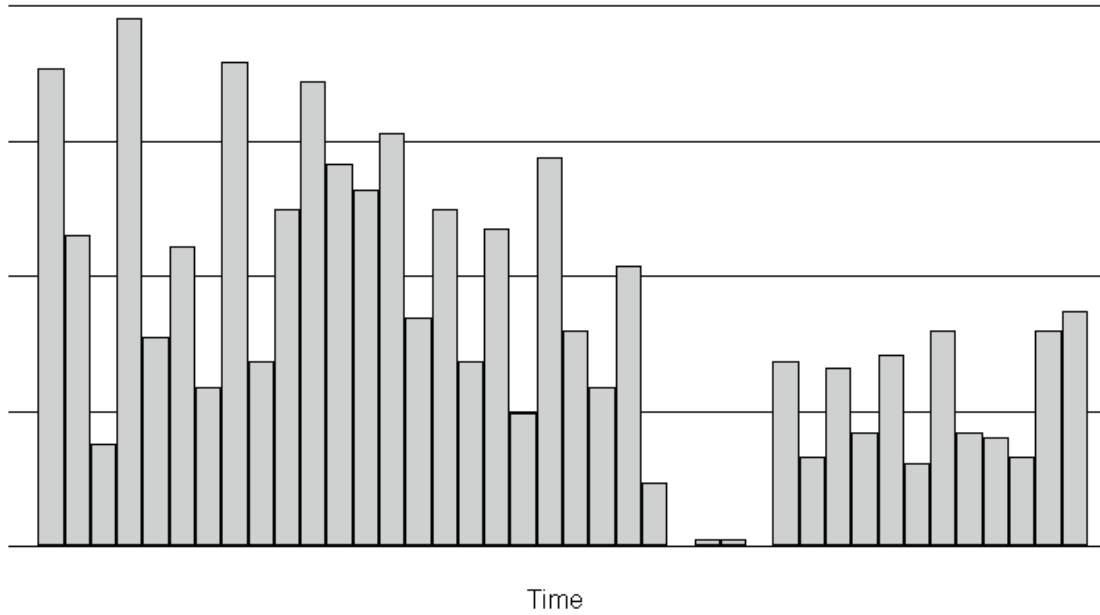
Table 93: Number of click-throughs per user (shopbot round 1)

<i>Total number of click- throughs</i>	<i>Number of users (Control)</i>	<i>Number of users (Treatment)</i>	<i>Total</i>
0	945	1039	1984
1	255	276	531
2	95	93	188
3	52	36	88
4	26	15	41
5	11	11	22
6	8	2	10
7	5	2	7
8	5	0	5
9	7	3	10
10	2	5	7
11	4	6	10
13	1	1	2
14	1	0	1
15	1	1	2
17	0	1	1
18	0	1	1
Total	1418	1492	2910

Pearson $\chi^2(16) = 25.4718$ Pr = 0.062

Appendix VI: shopbot experiment round 2

Figure 37: Click-throughs over time (shopbot round 2)



Due to proprietary information concerns, more detailed data cannot be disclosed here.

Table 94: Randomization check for users and clicks (shopbot round 2)

	(1)	(2)	<i>Treatment</i> (3)	(4)	(5)
	All users	All clicks	Freezers	Fridge-f.	Fridges
linux	0.00740 (0.135)	0.0789 (0.297)			0.184 (0.299)
mac	0.000752 (0.0976)	0.435*** (0.130)	-0.333 (0.574)	0.122 (0.242)	0.650*** (0.159)
msie523	-0.472 (0.509)	-0.689 (0.508)		-0.592 (0.547)	
msie55	0.0570 (0.0981)	0.523*** (0.141)	0.167 (0.454)	-0.136 (0.326)	0.773*** (0.167)
msie60	0.0367 (0.0487)	0.217** (0.0804)	0.222 (0.290)	-0.0624 (0.159)	0.322** (0.0988)
firefox10	0.0314 (0.0654)	0.126 (0.0983)	-0.0833 (0.321)	0.0690 (0.183)	0.153 (0.129)
firefox15	0.0246 (0.0518)	0.261** (0.0829)	0.238 (0.293)	0.0211 (0.163)	0.356*** (0.103)
netscape	0.0567 (0.137)	0.0427 (0.213)		-0.469 (0.384)	0.270 (0.256)
opera	0.0307 (0.0751)	-0.0192 (0.144)	0.667 (0.454)	-0.327 (0.243)	-0.0247 (0.199)
google	0.00240 (0.0222)				
referrerDE	-0.0151 (0.0328)				
referrerAT	-0.0734 (0.170)				
referrerCH	0.0430 (0.168)				
Prob > F	0.999	0.000	0.247	0.419	0.000
adj. R-sq	-0.005	0.015	0.008	0.001	0.035
N	2357	1391	250	329	812

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Models 3 to 5 include click-throughs to the respective appliance categories. The four last coefficients in model 1 refer to search paths through which users initially arrived at the experimental website.

Table 95: Cookie acceptance (shopbot round 2)

<i>Cookie type</i>	<i>Control</i>	<i>Treatment</i>	<i>Total</i>
<i>All users</i>			
Persistent %	96.8	96.8	96.8
Temporary %	3.2	3.2	3.2
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0013 Pr = 0.971			
<i>Freezers</i>			
Persistent %	99.1	99.1	99.1
Temporary %	0.9	0.9	0.9
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0002 Pr = 0.989			
<i>Fridge-freezers</i>			
Persistent %	97.0	96.6	96.8
Temporary %	3.0	3.4	3.2
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0613 Pr = 0.804			
<i>Refrigerators</i>			
Persistent %	96.3	96.7	96.5
Temporary %	3.7	3.3	3.5
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.1676 Pr = 0.682			

Table 96: Variety in products, brands, and final retailers shown (shopbot round 2)

<i>Cooling appliance category</i>	<i>Number of different products shown</i>	<i>Number of different brands shown</i>	<i>Number of different final retailers shown</i>
<i>Freezers (Overall)</i>			
Control	261	24	30
Treatment	262	25	30
<i>Fridge-freezers (Overall)</i>			
Control	518	30	29
Treatment	518	30	29
<i>Refrigerators (Overall)</i>			
Control	1011	30	35
Treatment	984	31	35

Figure 38: Prices and life-cycle costs of all freezers shown (shopbot round 2)

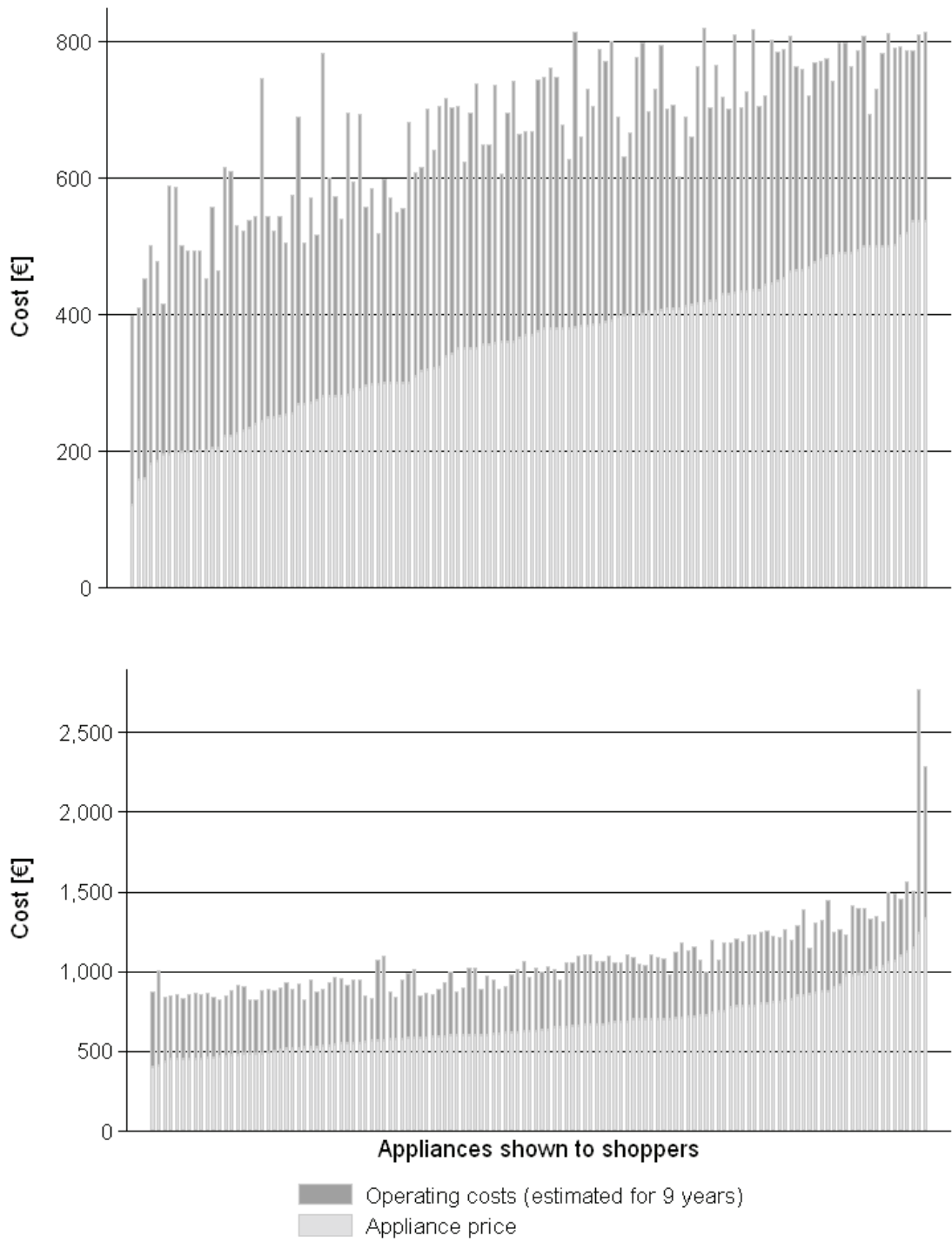
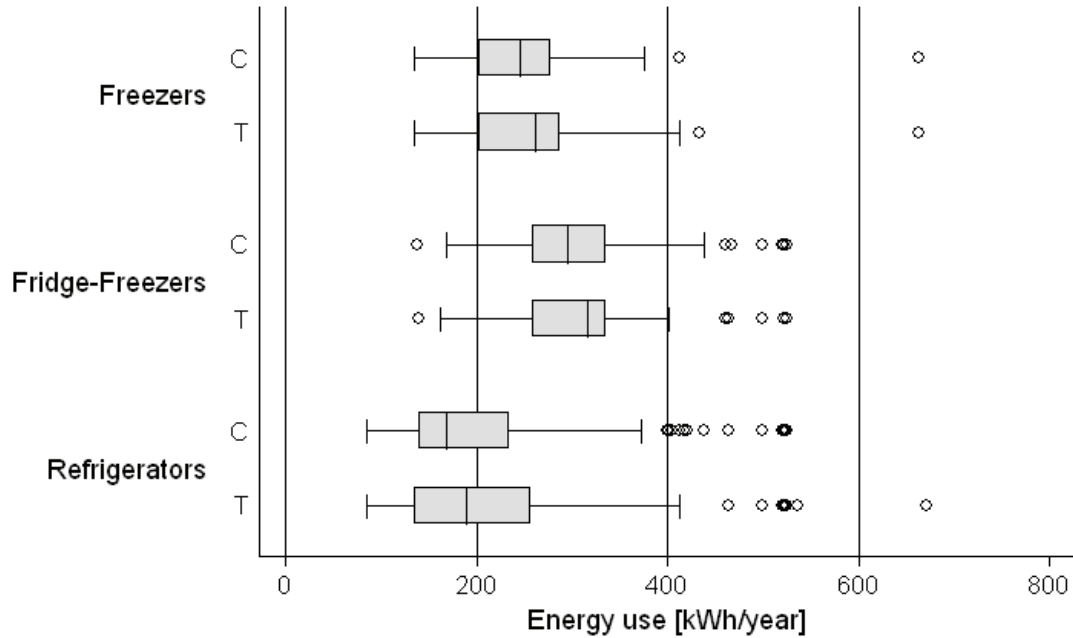


Table 97: Total number of click-throughs per user (shopbot round 2)

Total number of click-throughs	Number of users (Control)	Number of users (Treatment)	Total
1	243	210	453
2	85	64	149
3	33	40	73
4	18	15	33
5	13	5	18
6	7	7	14
7	3	3	6
8	3	5	8
9	4	1	5
10	1	4	5
11	2	1	3
12	0	1	1
13	0	1	1
16	0	1	1
17	1	0	1
18	0	1	1
22	1	1	2
23	1	0	1
31	1	1	2
Total	416	361	777

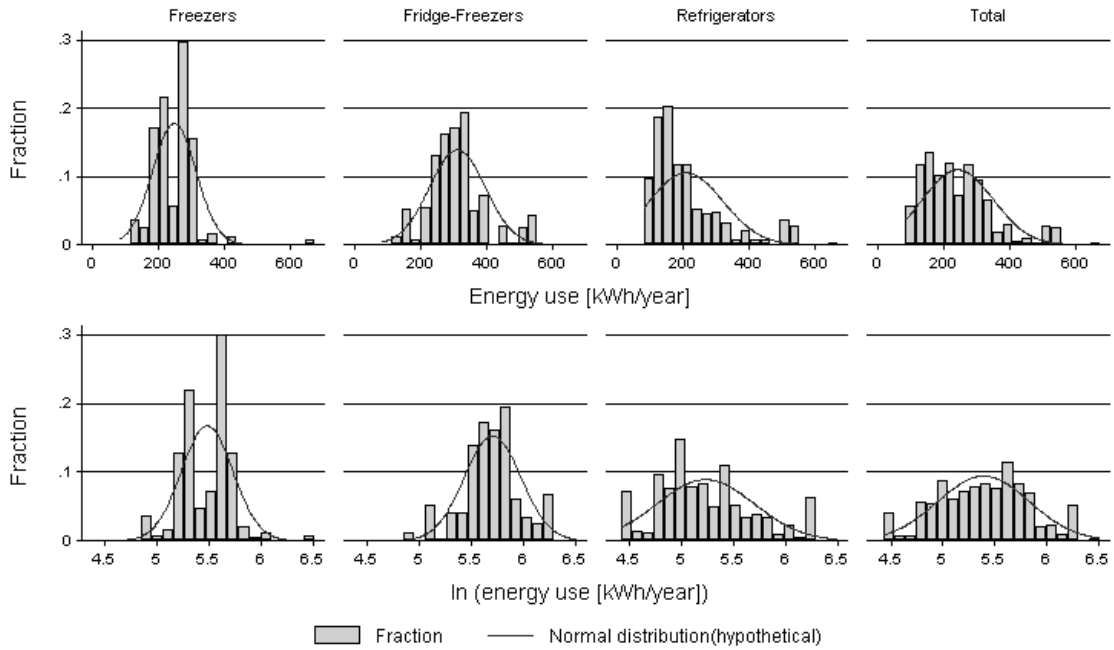
Note: Users with more than 20 click-throughs were not included in subsequent analyses.

Figure 39: Energy use box plots for clicked appliances (shopbot round 2)



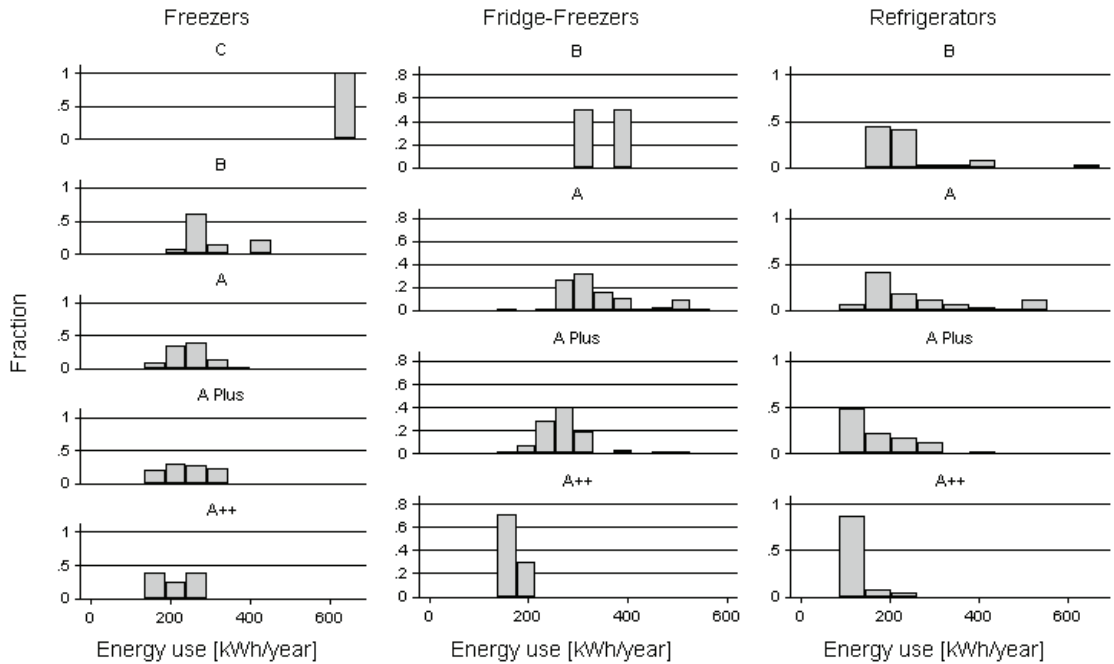
Note: N(total)=1391; C-Control; T-Treatment

Figure 40: Energy use histograms for clicked appliances (shopbot round 2)



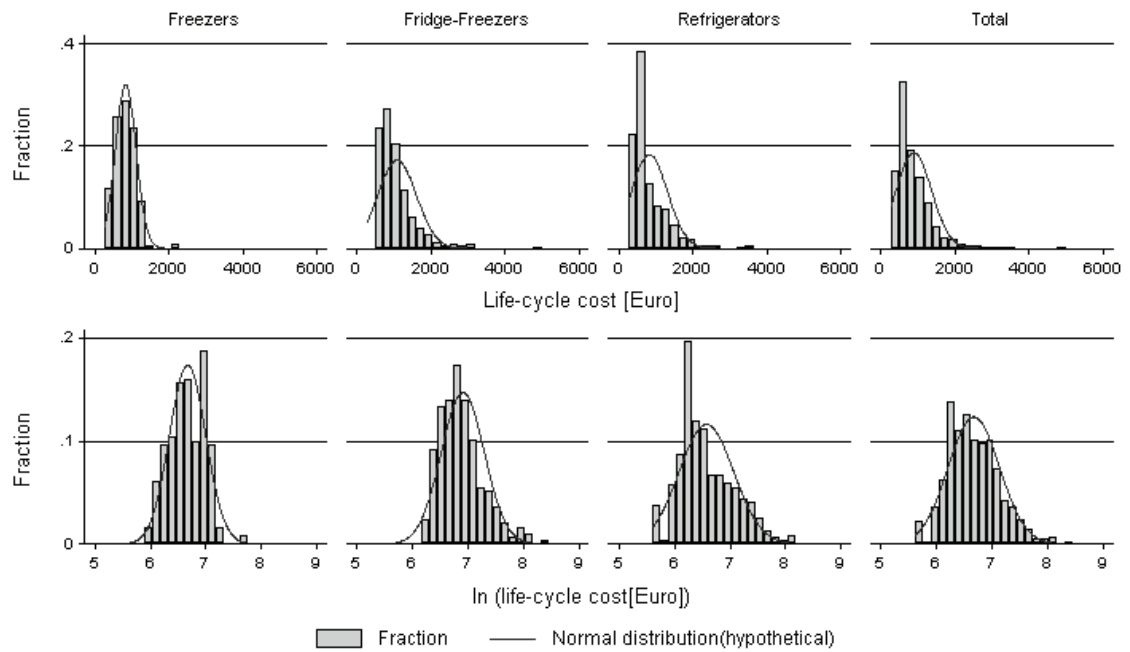
N(total)=1391

Figure 41: Energy efficiency classes by appliance types (shopbot round 2)



N(total)=1391

Figure 42: Life-cycle cost histograms for clicked appliances (shopbot round 2)



N(total)=1391

Table 98: Price quartiles for clicked appliances (shopbot round 2)

	<i>N</i>	<i>Min.</i> price	<i>p25%</i> price	<i>p50%</i> price	<i>p75%</i> price	<i>Max.</i> price
<i>Freezers</i>						
Control	114	159	325	447	619	1329
Treatment	136	120	279	415	669	1329
Total	250	120	299	432	650	1329
<i>Fridge-freezers</i>						
Control	187	32	345	489	750	2049
Treatment	142	30	385	498	869	4019
Total	329	30	379	492	786	4019
<i>Refrigerators</i>						
Control	429	105	265	399	669	2569
Treatment	383	32	250	436	679	2899
Total	812	32	254	409	669	2899
<i>Overall</i>						
Control	730	32	299	441	669	2569
Treatment	661	30	280	449	699	4019
Total	1391	30	290	449	695	4019

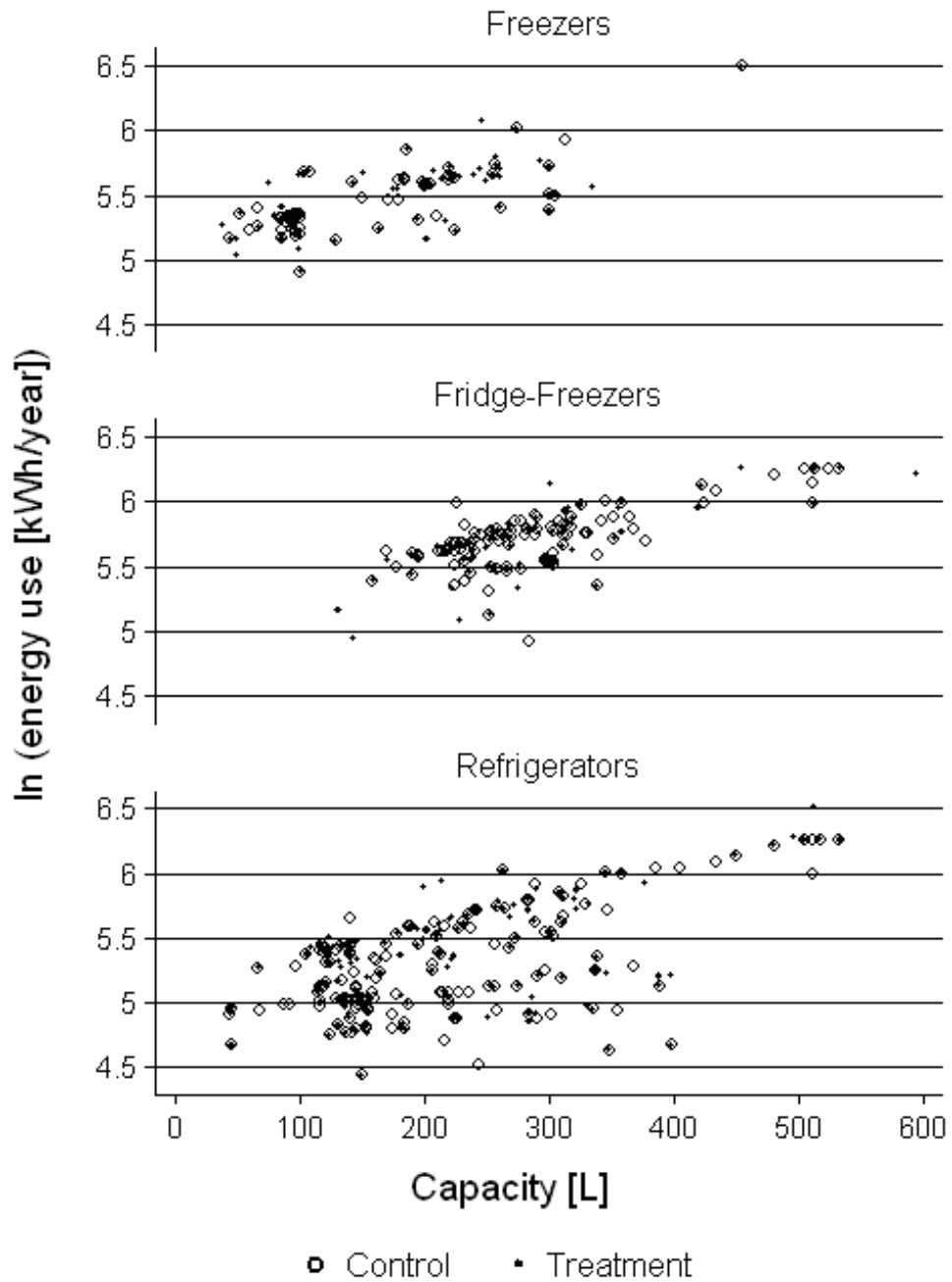
Note: Prices in [Euro]

Table 99: Capacity quartiles for clicked appliances (shopbot round 2)

	<i>N</i>	<i>Min.</i> capacity	<i>p25%</i> capacity	<i>p50%</i> capacity	<i>p75%</i> capacity	<i>Max.</i> capacity
<i>Freezers</i>						
Control	114	45	100	184	220	454
Treatment	136	38	100	198	225	454
Total	250	38	100	195	224	454
<i>Fridge-freezers</i>						
Control	187	159	233	278	318	532
Treatment	142	131	253	283	318	594
Total	329	131	249	283	318	594
<i>Refrigerators</i>						
Control	429	45	137	160	275	532
Treatment	383	45	140	189	288	532
Total	812	45	140	175	284	532
<i>Overall</i>						
Control	730	45	145	216	290	532
Treatment	661	38	145	221	291	594
Total	1391	38	145	220	291	594

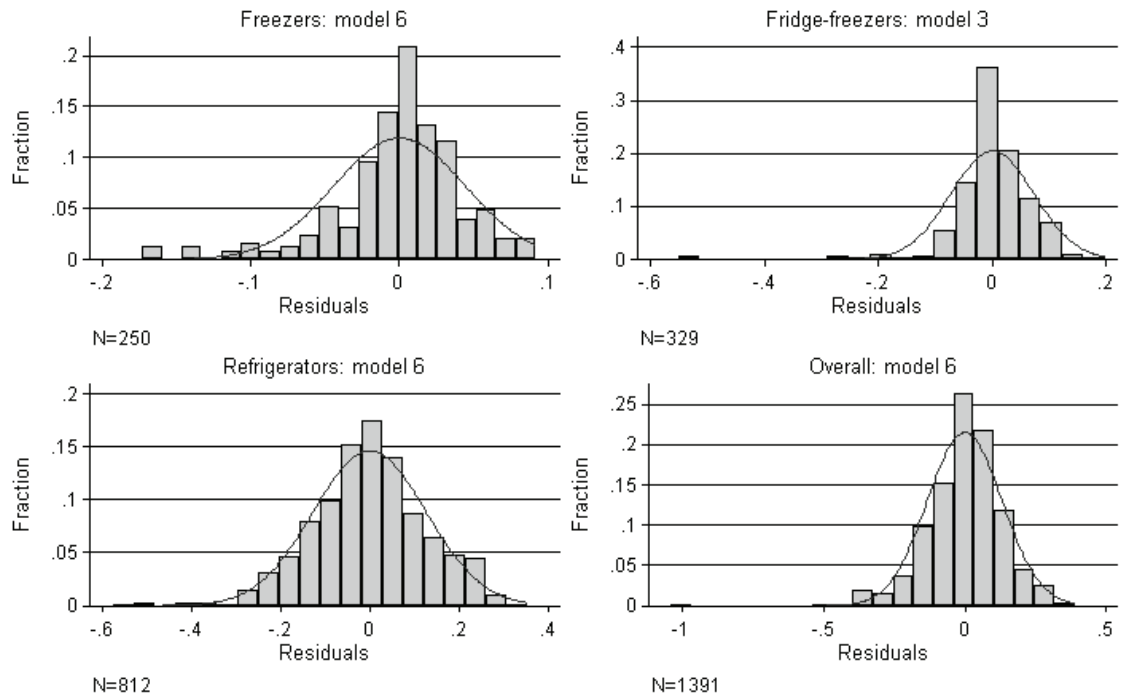
Note: Capacity in [L].

Figure 43: Energy vs. capacity scatter plots for appliances (shopbot round 2)



N(total)=1391

Figure 44: Residuals of selected models (shopbot round 2)



Note: Residuals of models with significant treatment coefficients.

Table 100: Assumed time horizon in the treatment group (shopbot round 2)

<i>Assumed time horizon [years]</i>	<i>No adjustment</i> (No. of users)	<i>Adjustment, no click-through</i> (No. of users)	<i>Adjustment and click-through(s)</i> (No. of users)	<i>Total</i>	
1	0	43	0	43	3.6%
5	0	4	2	6	0.5%
9*	1145	0	0	1145	95.9%
Total	1145	47	2	1194	100.0%

Note: *default

Table 101: Sorting by life-cycle cost in the treatment group (shopbot round 2)

<i>Function with respect to life-cycle cost</i>	<i>Function off</i> (No. of users)	<i>Function on, no click-through</i> (No. of users)	<i>Function on, click-through(s)</i> (No. of users)	<i>Total</i>
Sorting	1183	6	5	1194
Filtering	1175	13	6	1194

Figure 45: Number of click-throughs per user (shopbot round 2)

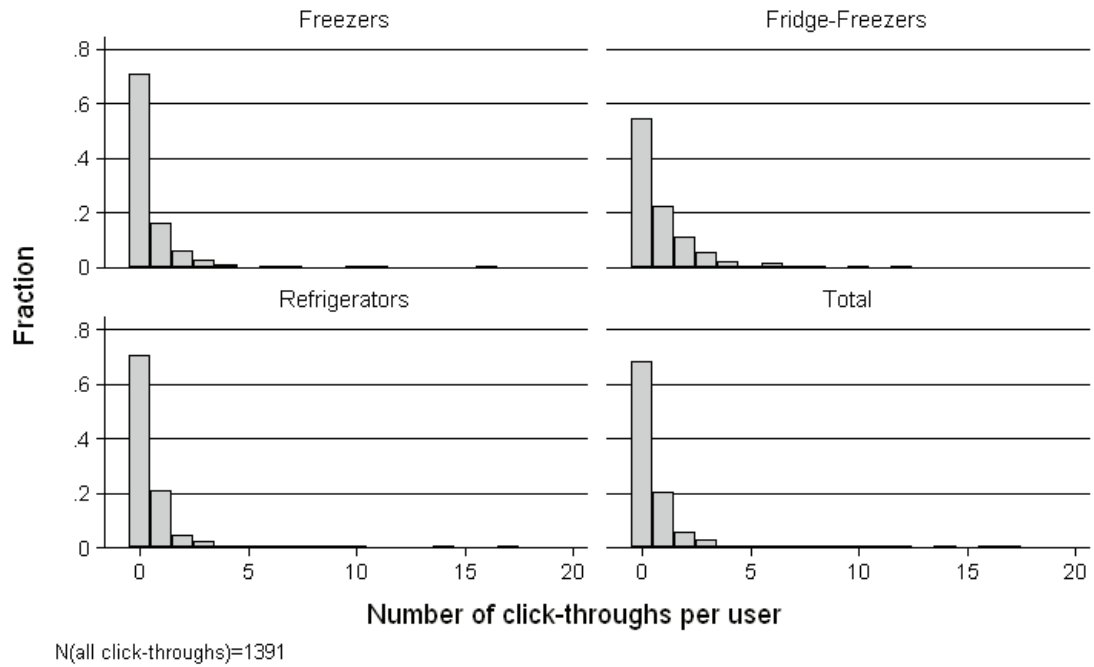


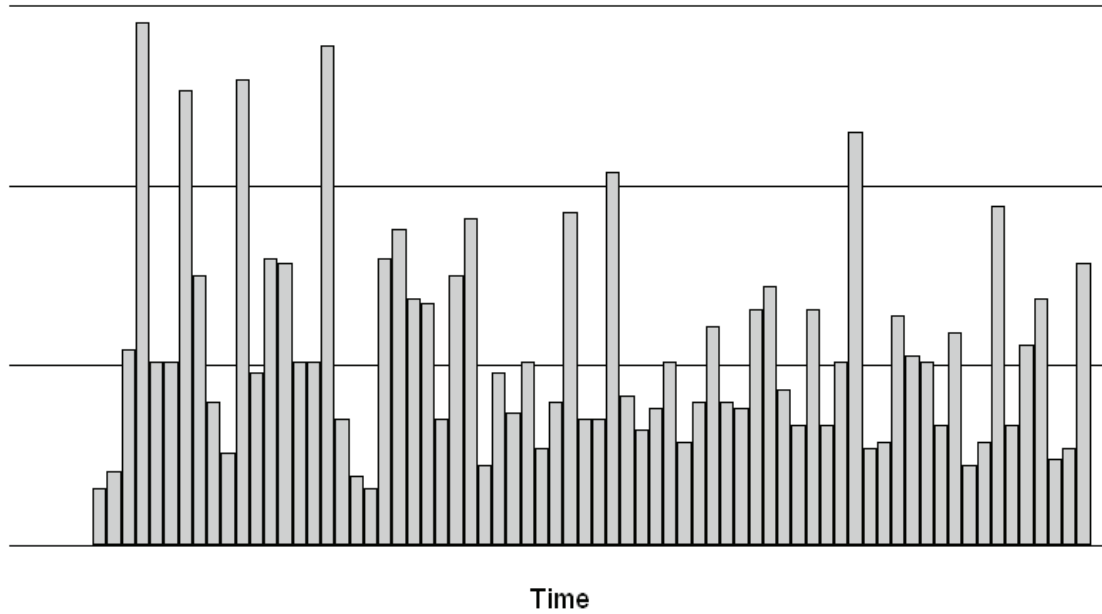
Table 102: Number of click-throughs per user (shopbot round 2)

<i>Total number of click-throughs</i>	<i>Number of users (Control)</i>	<i>Number of users (Treatment)</i>	<i>Total</i>
0	771	852	1623
1	246	221	467
2	75	58	133
3	31	32	63
4	12	7	19
5	9	3	12
6	7	4	11
7	3	5	8
8	5	4	9
9	0	2	2
10	2	2	4
11	1	1	2
12	0	1	1
14	1	0	1
16	0	1	1
17	0	1	1
Total	1163	1194	2357

Pearson chi2(15) = 18.9103 Pr = 0.218

Appendix VII: online shop experiment round 1

Figure 46: Click-throughs over time (online shop round 1)



Due to proprietary information concerns, more detailed data cannot be disclosed here.

Table 103: Randomization check for users and clicks (online shop round 1)

	<i>Treatment</i>					
	(1) All users	(2) Users w/pref	(3) All clicks	(4) Final CT	(5) SimpleSearch	(6) ExpertSearch
linux	-0.0412 (0.0393)	-0.0326 (0.0474)	-0.142 (0.151)	-0.173 (0.161)	-0.150 (0.287)	-0.107 (0.178)
mac	-0.0183 (0.0275)	-0.0145 (0.0340)	-0.291** (0.106)	-0.165 (0.123)	-0.484** (0.165)	-0.173 (0.142)
msie55	0.0573 (0.0327)	0.0496 (0.0423)	-0.509*** (0.0860)	-0.242 (0.126)	-0.368** (0.135)	-0.485*** (0.117)
msie60	-0.00279 (0.00551)	-0.00490 (0.0134)	-0.204*** (0.0554)	-0.0718 (0.0810)	-0.247** (0.0781)	-0.169* (0.0793)
firefox10	0.0112 (0.0142)	0.0113 (0.0201)	-0.223*** (0.0662)	-0.110 (0.0926)	-0.216* (0.0933)	-0.246** (0.0944)
firefox15	0.00616 (0.0105)	0.00821 (0.0168)	-0.231*** (0.0600)	-0.0826 (0.0858)	-0.275** (0.0855)	-0.180* (0.0851)
netscape	0.0282 (0.0393)	0.0108 (0.0493)	-0.00351 (0.135)	0.142 (0.160)	-0.166 (0.234)	0.0858 (0.168)
opera	0.0363 (0.0274)	0.0494 (0.0346)	-0.273* (0.109)	-0.0879 (0.131)	-0.329* (0.167)	-0.204 (0.146)
preferences	No	Yes	No	No	Yes	No
Prob > F	0.453	0.693	0.000	0.328	0.000	0.004
adj. R-sq	-0.000	-0.000	0.014	0.001	0.025	0.013
N	46422	41991	2386	1484	1235	1151

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CT: Click-through. SimpleS: Simple search recommendation mode. ExpertS: Expert search recommendation mode

Table 104: Cookie acceptance (online shop round 1)

<i>Cookie type</i>	<i>Control</i>	<i>Treatment</i>	<i>Total</i>
<i>All users</i>			
Persistent %	99.9	99.9	99.9
Temporary %	0.1	0.1	0.1
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.3417 Pr = 0.559			
<i>All clicks</i>			
Persistent %	97.2	96.4	96.8
Temporary %	2.8	3.6	3.2
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.4990 Pr = 0.480			
<i>SimpleSearch</i>			
Persistent %	100.0	100.0	100.0
Total %	100.0	100.0	100.0
<i>ExpertSearch</i>			
Persistent %	94.3	92.1	93.3
Temporary %	5.7	7.9	6.7
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.8612 Pr = 0.353			

Table 105: Variety in products and brands shown (online shop round 1)

<i>Recommendation mode</i>	<i>Number of different products shown</i>	<i>Number of different brands shown</i>
<i>Simple search</i>		
Control	152	7
Treatment	150	7
<i>Expert search</i>		
Control	152	7
Treatment	152	7

Figure 47: Prices and life-cycle costs of appliances shown (online shop round 1)

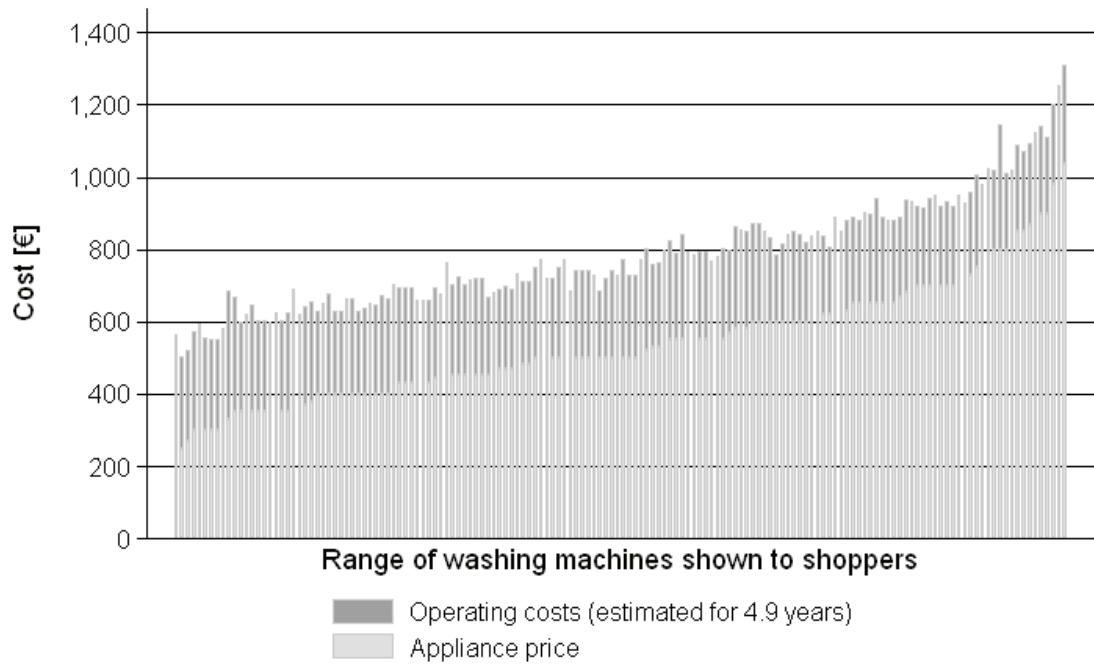
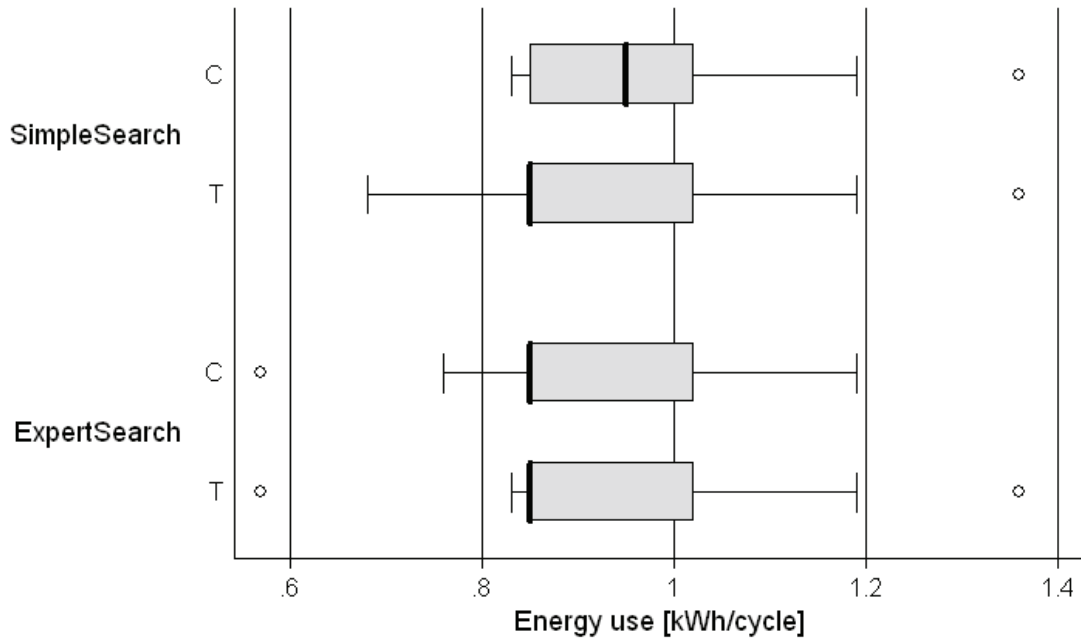


Table 106: Total number of click-throughs per user (online shop round 1)

<i>Total number of click-throughs</i>	<i>Number of users (Control)</i>	<i>Number of users (Treatment)</i>	<i>Total</i>
1	323	286	609
2	199	184	383
3	86	85	171
4	66	53	119
5	48	42	90
6	37	32	69
7	13	12	25
8	22	14	36
9	15	11	26
10	4	6	10
11	5	7	12
12	7	4	11
13	2	4	6
14	3	4	7
15	2	3	5
16	2	1	3
17	4	0	4
18	1	0	1
19	1	2	3
20	2	0	2
21	1	1	2
23	3	2	5
24	4	0	4
25	2	0	2
26	1	0	1
29	1	0	1
35	0	1	1
38	0	1	1
42	0	1	1
69	1	0	1
Total	855	756	1611

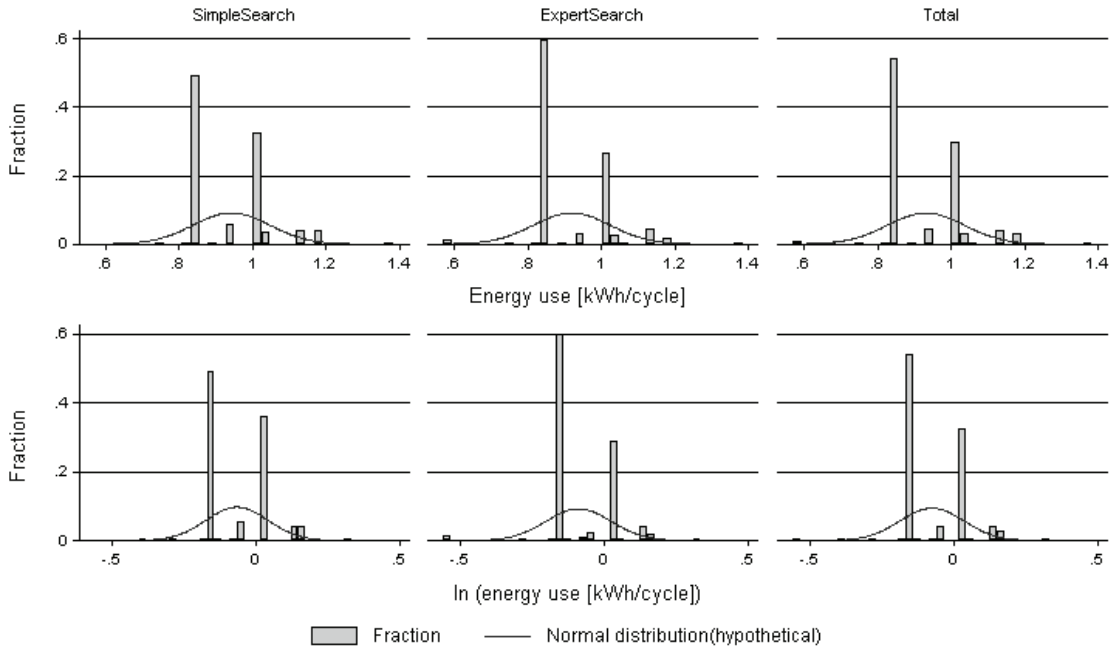
Note: Users with more than 20 click-throughs were not included in subsequent analyses.

Figure 48: Energy use box plots for clicked appliances (online shop round 1)



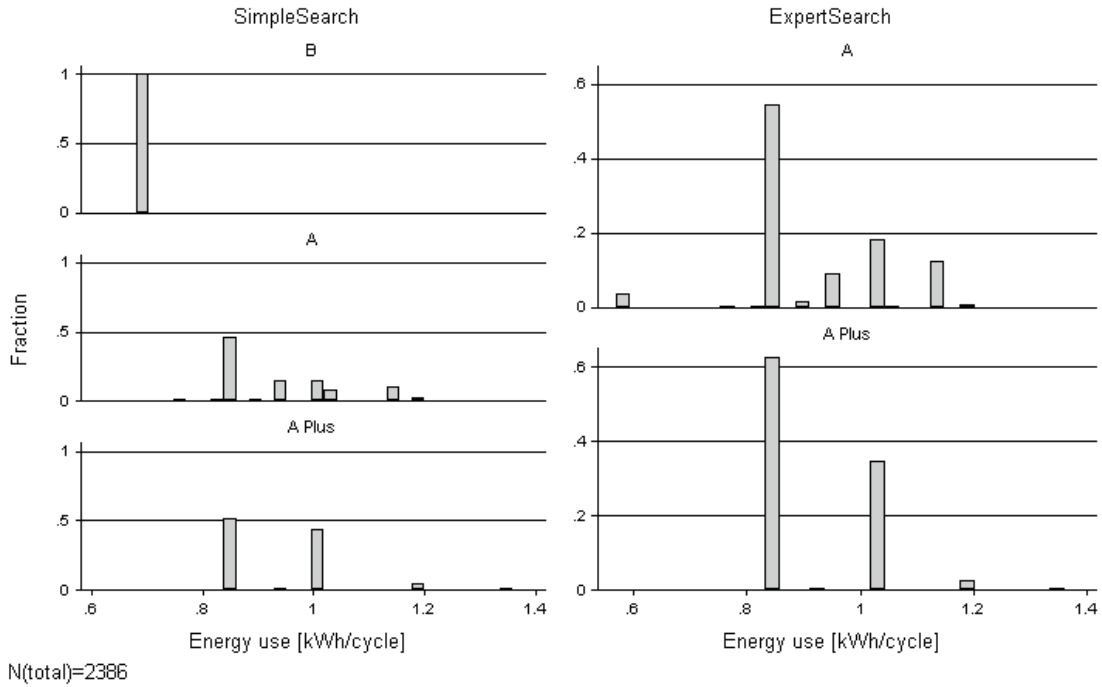
Note: N(total)=2386; C-Control; T-Treatment

Figure 49: Energy use histograms for clicked appliances (online shop round 1)



N(total)=2386

Figure 50: Energy efficiency classes by appliance types (online shop round 1)



Note: The “A Plus” category did not exist for washing machines at the time of the experiment. It is a supplementary label indicating high energy efficiency and developed by the retailer himself.

Figure 51: Water use histograms for clicked appliances (online shop round 1)

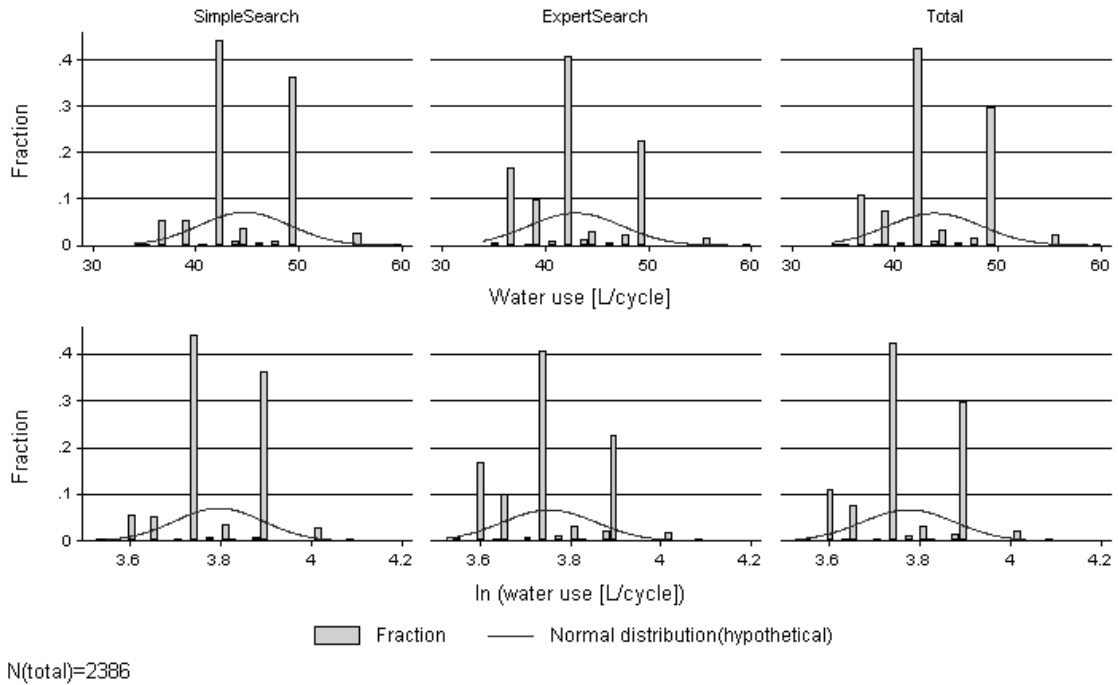
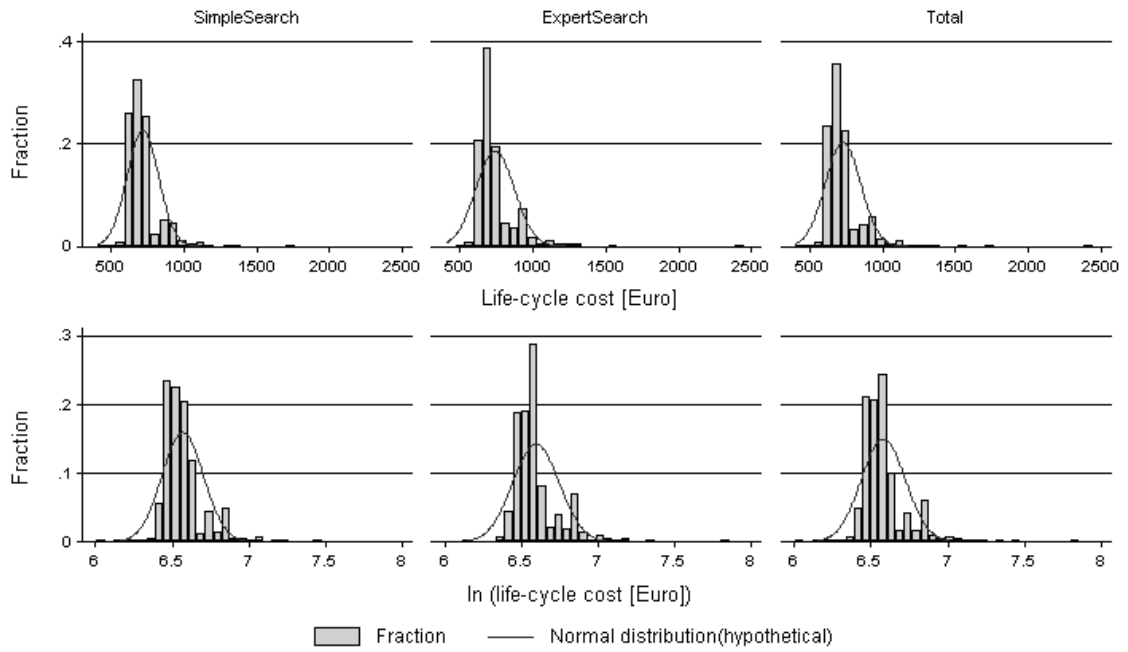


Figure 52: Life-cycle cost histograms for clicked appliances (online shop round 1)



N(total)=2386

Table 107: Price quartiles for clicked appliances (online shop round 1)

	<i>N</i>	<i>Min.</i> price	<i>p25%</i> price	<i>p50%</i> price	<i>p75%</i> price	<i>Max.</i> price
<i>Simple search</i>						
Control	624	350	400	450	500	1039
Treatment	611	350	400	450	500	900
Total	1235	350	400	450	500	1039
<i>Expert search</i>						
Control	617	350	400	480	500	1039
Treatment	534	300	400	500	500	1039
Total	1151	300	400	500	500	1039
<i>Overall</i>						
Control	1241	350	400	450	500	1039
Treatment	1145	300	400	450	500	1039
Total	2386	300	400	450	500	1039

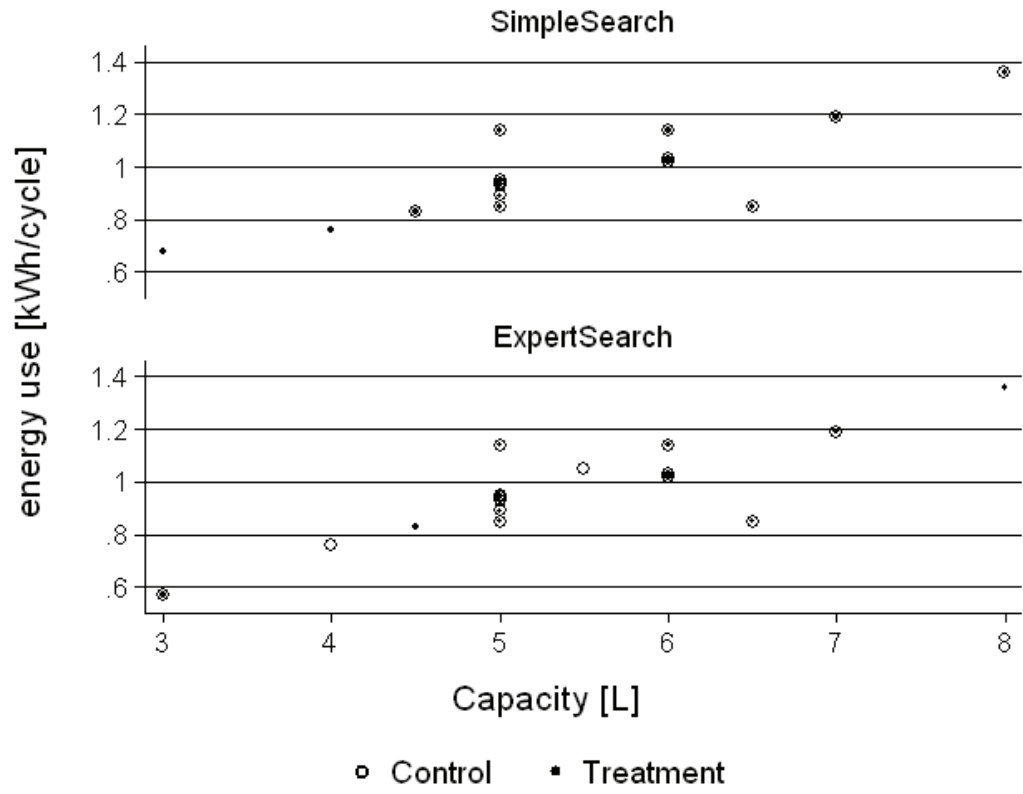
Note: Price in [Euro]

Table 108: Capacity quartiles for clicked appliances (online shop round 1)

	<i>N</i>	<i>Min.</i> capacity	<i>p25%</i> capacity	<i>p50%</i> capacity	<i>p75%</i> capacity	<i>Max.</i> capacity
<i>Simple search</i>						
Control	624	5	5	6	6	8
Treatment	611	3	5	6	6	8
Total	1235	3	5	6	6	8
<i>Expert search</i>						
Control	617	3	5	5	6	7
Treatment	534	3	5	5	6	8
Total	1151	3	5	5	6	8
<i>Overall</i>						
Control	1241	3	5	5	6	8
Treatment	1145	3	5	5	6	8
Total	2386	3	5	5	6	8

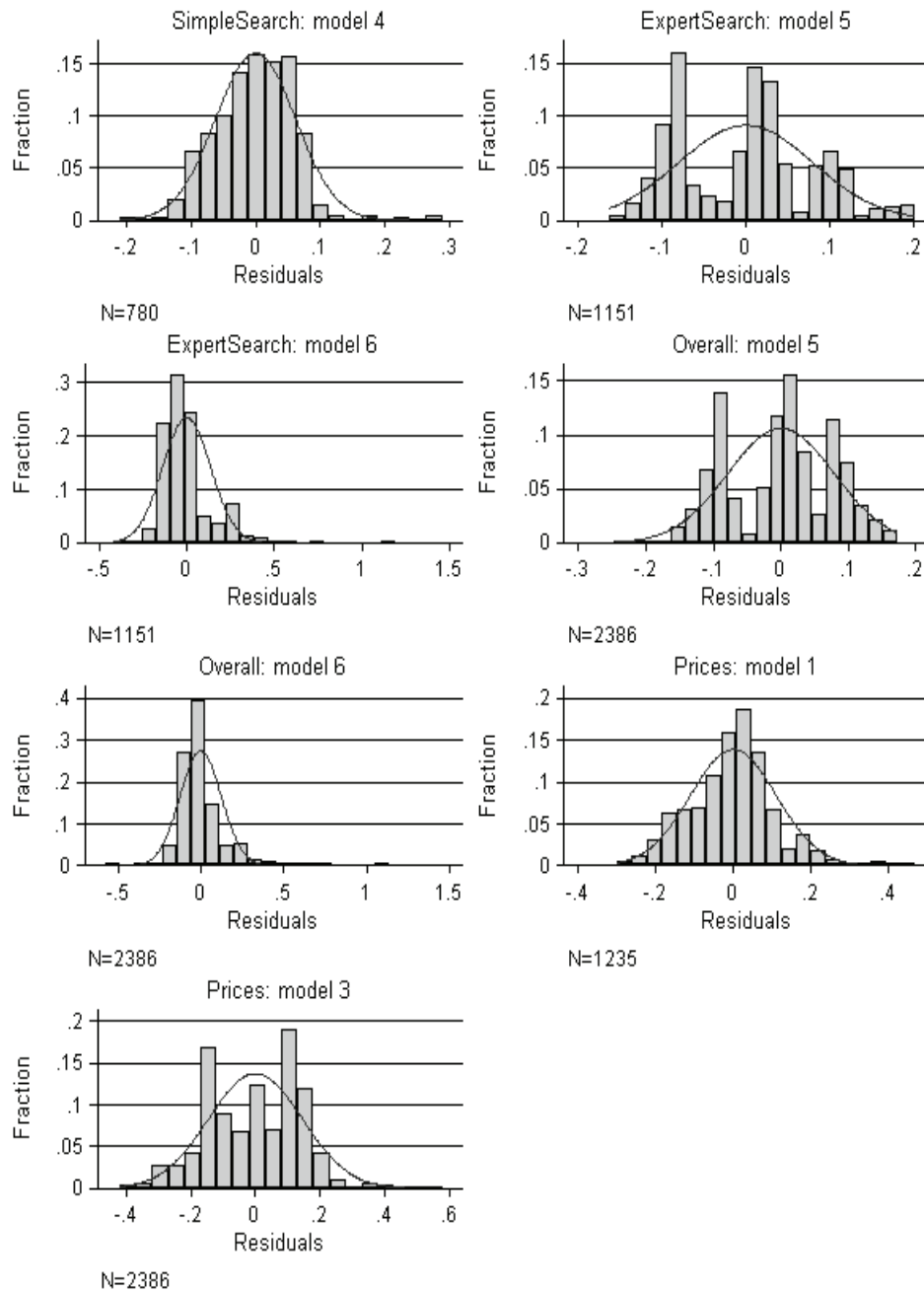
Note: Capacity in [L]

Figure 53: Energy vs. capacity scatter plots by search mode (online shop round 1)



N(total)=2386

Figure 54: Residuals of selected models (online shop round 1)



Note: Residuals of models with significant treatment coefficients.

Table 109: Effect size index f^2 for linear regression models (online shop round 1)

<i>Mode</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>	<i>Model 6</i>
Simple search				0.0086		
Expert search					0.0049	0.0092
Overall					0.0021	0.0030

Note: Effect sizes only from those models with significant ($p < 0.05$) treatment coefficient(s).
 $f^2 = (R^2_{\text{treatment variables}} - R^2_{\text{no treatment variables}}) / (1 - R^2_{\text{treatment variables}})$. (Cohen 1977, 410-413)

Table 110: Assumed time horizon in the treatment group (online shop round 1)

<i>Assumed time horizon [years]</i>	<i>No adjustment (No. of users)</i>	<i>Adjustment, no click-through (No. of users)</i>	<i>Adjustment and click-through(s) (No. of users)</i>	<i>Total</i>	
0	0	3	0	3	0.0%
1	0	29	7	36	0.2%
2	0	1	0	1	0.0%
2.5	0	1	0	1	0.0%
3	0	2	0	2	0.0%
4	0	4	1	5	0.0%
4.9*	22837	0	0	22837	98.3%
5	0	23	4	27	0.1%
6	0	11	2	13	0.1%
7	0	7	3	10	0.0%
7.9	0	1	0	1	0.0%
8	0	16	2	18	0.1%
8.5	0	1	0	1	0.0%
9	0	180	4	184	0.8%
9.5	0	1	0	1	0.0%
10	0	64	11	75	0.3%
12	0	2	0	2	0.0%
15	0	9	0	9	0.0%
20	0	1	0	1	0.0%
Total	22837	356	34	23227	100.00%

Note: * default time horizon

Table 111: Assumed usage frequency in the treatment group (online shop round 1)

<i>Assumed usage frequency [times per week]</i>	<i>No adjustment</i> (No. of users)	<i>Adjustment, no click-through</i> (No. of users)	<i>Adjustment and click-through(s)</i> (No. of users)	<i>Total</i>	
0	0	5	0	5	0.0%
0.5	0	2	0	2	0.0%
1	0	69	8	77	0.3%
1.2	0	1	0	1	0.0%
1.4	0	1	0	1	0.0%
1.5	0	7	2	9	0.0%
2	0	61	12	73	0.3%
2.5	0	3	0	3	0.0%
3*	22905	0	0	22905	98.6%
3.5	0	1	0	1	0.0%
4	0	26	5	31	0.1%
5	0	44	10	54	0.2%
5.5	0	1	0	1	0.0%
6	0	18	7	25	0.1%
6.5	0	1	0	1	0.0%
7	0	16	2	18	0.1%
8	0	3	1	4	0.0%
9	0	2	1	3	0.0%
10	0	7	0	7	0.0%
12	0	1	1	2	0.0%
15	0	1	1	2	0.0%
20	0	1	0	1	0.0%
30	0	1	0	1	0.0%
Total	22905	272	50	23227	100.0%

Note: * default usage frequency

Table 112: Robustness check for life-cycle cost (online shop round 1)

	<i>ln(lccost)</i>					
	(1) Ssearch	(2) Ssearch	(3) Esearch	(4) Esearch	(5) Overall	(6) Overall
treatment	0.0037 (0.0057)	0.0000046 (0.0042)	0.027** (0.0085)	0.010 (0.0072)	0.014** (0.0053)	0.0034 (0.0043)
ln(capacity)	0.31*** (0.037)	0.32*** (0.028)	0.17*** (0.032)	0.16*** (0.029)	0.34*** (0.031)	0.32*** (0.028)
mode					0.031*** (0.0053)	0.025*** (0.0044)
constant	6.31*** (0.16)	6.27*** (0.13)	6.62*** (0.060)	6.71*** (0.049)	5.74*** (0.13)	5.79*** (0.12)
efficiency class	Yes	Yes	Yes	Yes	Yes	Yes
brands	Yes	Yes	Yes	Yes	Yes	Yes
other features	Yes	Yes	Yes	Yes	Yes	Yes
preferences	Yes	Yes	No	No	No	No
adj. R-sq	0.480	0.619	0.180	0.236	0.256	0.331
N	1235	1235	1151	1151	2386	2386

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, models (1), (3), and (5): life-cycle cost based on user-adjusted assumptions (treatment) versus common default assumptions (control); models (2), (4), and (6): life-cycle cost based on common default assumptions for both experimental groups

Table 113: Number of click-throughs per user (online shop round 1)

<i>Total number of click- throughs</i>	<i>Number of users (Control)</i>		<i>Number of users (Treatment)</i>		<i>Total</i>	
0	22411	96.6%	22527	97.0%	44938	96.8%
1	546	2.4%	469	2.0%	1015	2.2%
2	145	0.6%	141	0.6%	286	0.6%
3	48	0.2%	42	0.2%	90	0.2%
4	16	0.1%	19	0.1%	35	0.1%
5	12	0.1%	13	0.1%	25	0.1%
6	7	0.0%	8	0.0%	15	0.0%
7	2	0.0%	2	0.0%	4	0.0%
8	5	0.0%	2	0.0%	7	0.0%
9	0	0.0%	1	0.0%	1	0.0%
10	1	0.0%	0	0.0%	1	0.0%
11	0	0.0%	2	0.0%	2	0.0%
12	1	0.0%	0	0.0%	1	0.0%
18	0	0.0%	1	0.0%	1	0.0%
19	1	0.0%	0	0.0%	1	0.0%
Total	23195	100.0%	23227	100.0%	46422	100.0%

Pearson $\chi^2(14) = 15.2242$ Pr = 0.363

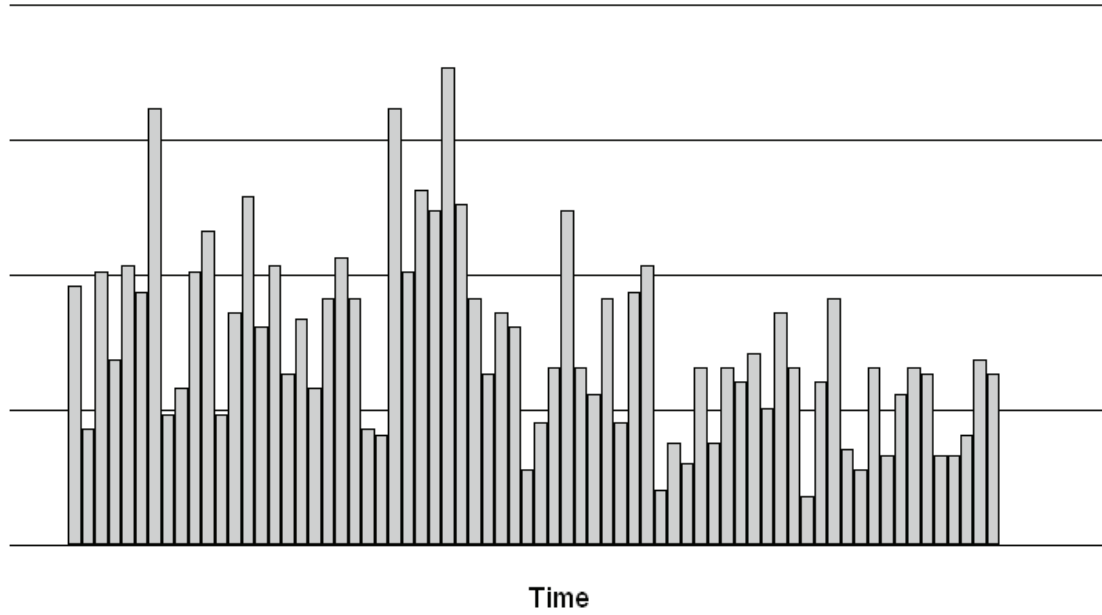
Table 114: Price cross-tabulations for all clicked appliances (online shop round 1)

<i>Price</i>	<i>Control</i>		<i>Treatment</i>		<i>Total</i>	
299.95	0	0.0%	5	0.4%	5	0.2%
349.95	62	5.0%	58	5.1%	120	5.0%
369.95	10	0.8%	3	0.3%	13	0.5%
379.95	6	0.5%	6	0.5%	12	0.5%
399	67	5.4%	47	4.1%	114	4.8%
399.95	327	26.3%	306	26.7%	633	26.5%
429.95	48	3.9%	41	3.6%	89	3.7%
444	0	0.0%	1	0.1%	1	0.0%
449	29	2.3%	18	1.6%	47	2.0%
449.95	119	9.6%	105	9.2%	224	9.4%
469.95	2	0.2%	1	0.1%	3	0.1%
479.95	6	0.5%	10	0.9%	16	0.7%
499.95	384	30.9%	350	30.6%	734	30.8%
529.95	3	0.2%	1	0.1%	4	0.2%
549.95	16	1.3%	25	2.2%	41	1.7%
579.95	15	1.2%	7	0.6%	22	0.9%
599.95	35	2.8%	28	2.4%	63	2.6%
619.95	11	0.9%	8	0.7%	19	0.8%
629.95	5	0.4%	7	0.6%	12	0.5%
649.95	13	1.0%	6	0.5%	19	0.8%
679.95	4	0.3%	10	0.9%	14	0.6%
699.95	51	4.1%	77	6.7%	128	5.4%
749.95	7	0.6%	5	0.4%	12	0.5%
799.95	7	0.6%	9	0.8%	16	0.7%
849.95	4	0.3%	0	0.0%	4	0.2%
899.95	6	0.5%	6	0.5%	12	0.5%
979.95	0	0.0%	1	0.1%	1	0.0%
999.95	1	0.1%	1	0.1%	2	0.1%
1039	3	0.2%	3	0.3%	6	0.3%
Total	1241	100.0%	1145	100.0%	2386	100.0%

Pearson $\chi^2(28) = 40.7041$ Pr = 0.057

Appendix VIII: online shop experiment round 2

Figure 55: Click-throughs over time (online shop round 2)



Due to proprietary information concerns, more detailed data cannot be disclosed here.

Table 115: Randomization check for users and clicks (online shop round 2)

	<i>Treatment</i>					
	(1) All users	(2) Users w/pref	(3) All clicks	(4) Final CT	(5) SimpleS CT	(6) ExpertS CT
linux	-0.00415 (0.0316)	0.0107 (0.0386)	-0.0701 (0.136)	-0.104 (0.147)	0.343 (0.226)	-0.262 (0.170)
mac	-0.0165 (0.0208)	-0.0217 (0.0264)	0.148* (0.0755)	0.0529 (0.0882)	0.406** (0.143)	0.0713 (0.0901)
msie55	-0.0400 (0.0304)	-0.0594 (0.0382)	-0.141 (0.109)	-0.102 (0.127)	-0.233 (0.180)	-0.168 (0.140)
msie60	0.00375 (0.00456)	0.00753 (0.0111)	-0.00236 (0.0562)	-0.0172 (0.0627)	-0.170 (0.109)	0.0329 (0.0672)
firefox10	0.000600 (0.0150)	-0.000771 (0.0196)	0.0286 (0.0711)	0.0117 (0.0839)	-0.106 (0.128)	0.0322 (0.0892)
firefox15	0.00749 (0.00782)	0.0110 (0.0133)	-0.00307 (0.0582)	0.0262 (0.0653)	-0.150 (0.112)	0.00745 (0.0705)
netscape	-0.0198 (0.0363)	-0.0145 (0.0444)	-0.00922 (0.144)	-0.00709 (0.168)	-0.00717 (0.207)	-0.159 (0.212)
opera	0.00793 (0.0228)	0.0112 (0.0287)	-0.141 (0.0944)	-0.149 (0.105)	-0.117 (0.169)	-0.221 (0.116)
preferences	No	Yes	No	No	Yes	No
Prob > F	0.826	0.842	0.216	0.621	0.057	0.108
adj. R-sq	-0.000	-0.000	0.001	-0.001	0.011	0.005
N	95388	89498	2065	1437	990	1075

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CT: Click-through. SimpleS: Simple search recommendation mode. ExpertS: Expert search recommendation mode

Table 116: Cookie acceptance (online shop round 2)

<i>Cookie type</i>	<i>Control</i>	<i>Treatment</i>	<i>Total</i>
<i>All users</i>			
Persistent %	99.9	99.9	99.9
Temporary %	0.1	0.1	0.1
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.7619 Pr = 0.383			
<i>All clicks</i>			
Persistent %	95.5	95.3	95.4
Temporary %	4.5	4.7	4.6
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.0161 Pr = 0.899			
<i>SimpleSearch</i>			
Persistent %	100.0	100.0	100.0
Total %	100.0	100.0	100.0
<i>ExpertSearch</i>			
Persistent %	91.8	90.2	91.0
Temporary %	8.2	9.8	9.0
Total %	100.0	100.0	100.0
Pearson chi2(1) = 0.3530 Pr = 0.552			

Table 117: Variety in products and brands shown (online shop round 2)

<i>Recommendation mode</i>	<i>Number of different products shown</i>	<i>Number of different brands shown</i>
<i>Simple search (Overall)</i>		
Control	162	7
Treatment	158	7
<i>Expert search (Overall)</i>		
Control	159	7
Treatment	162	7

Figure 56: Prices and life-cycle costs of appliances shown (online shop round 2)

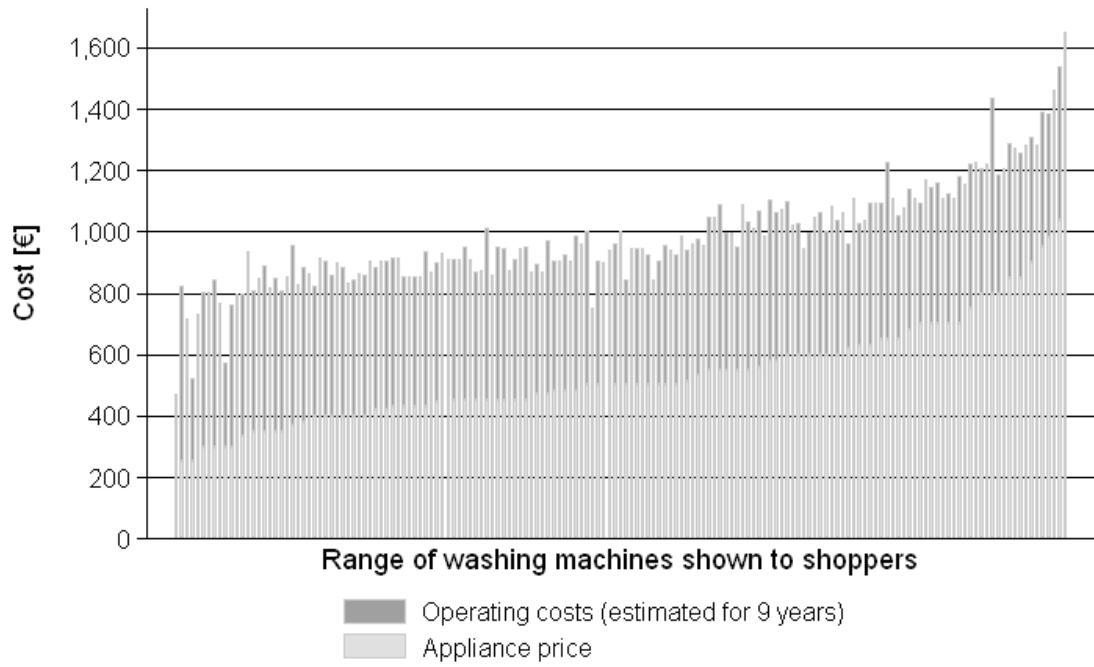
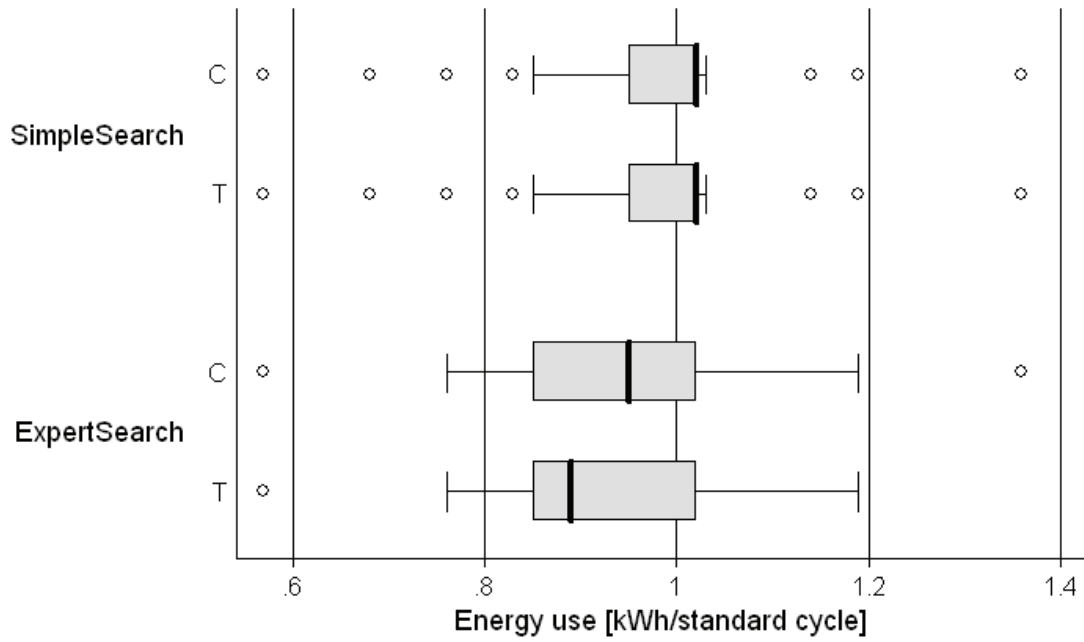


Table 118: Total number of click-throughs per user (online shop round 2)

<i>Total number of click-throughs</i>	<i>Number of users (Control)</i>	<i>Number of users (Treatment)</i>	<i>Total</i>
1	425	379	804
2	145	184	329
3	85	80	165
4	54	43	97
5	33	31	64
6	17	20	37
7	10	10	20
8	9	11	20
9	7	5	12
10	6	1	7
11	5	6	11
12	0	3	3
13	1	7	8
14	2	0	2
15	1	4	5
16	1	1	2
17	2	5	7
19	0	2	2
20	0	1	1
21	2	1	3
23	2	2	4
46	1	0	1
49	1	0	1
Total	809	796	1605

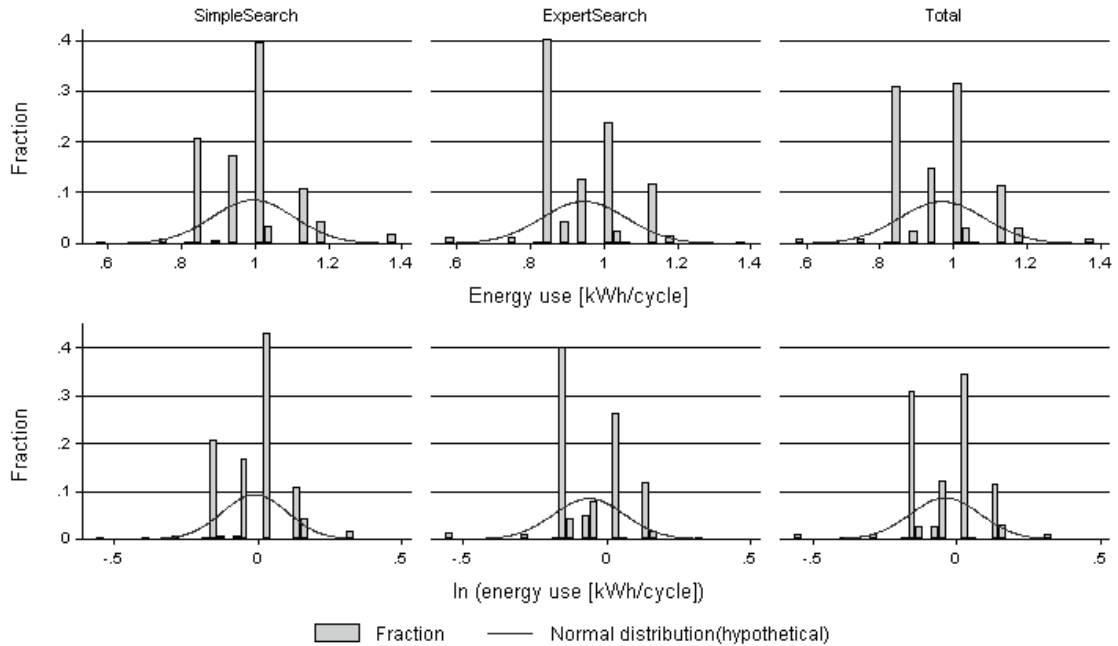
Note: Users with more than 20 click-throughs were not included in subsequent analyses.

Figure 57: Energy use box plots for clicked appliances (online shop round 2)



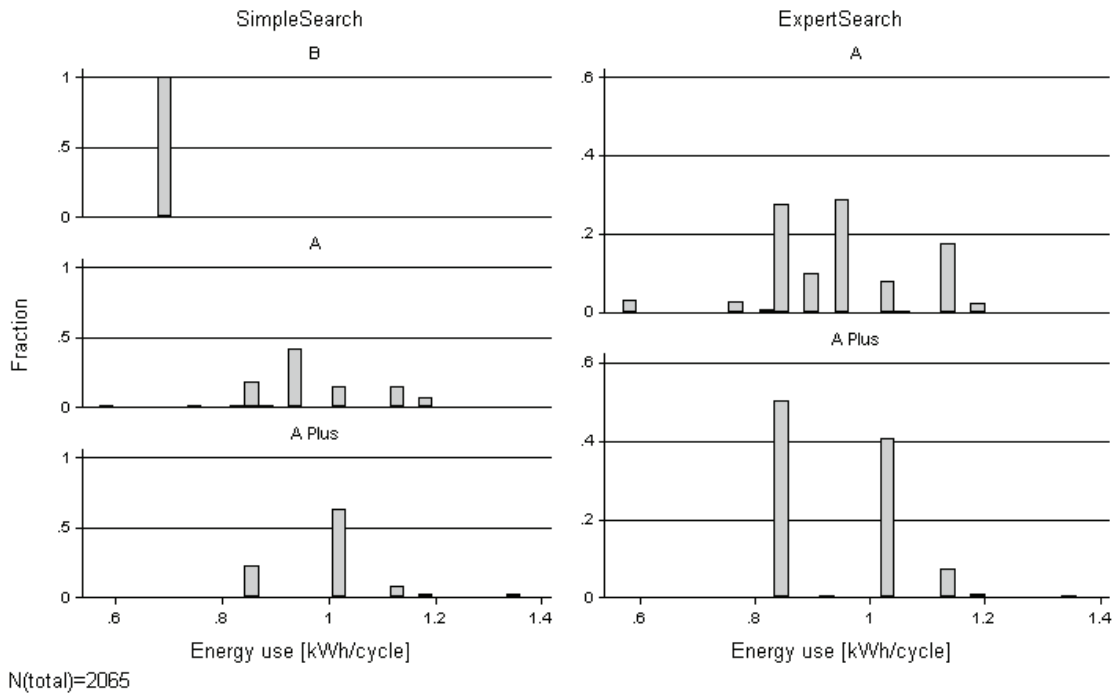
Note: N(total)=2065; C-Control; T-Treatment

Figure 58: Energy use histograms for clicked appliances (online shop round 2)



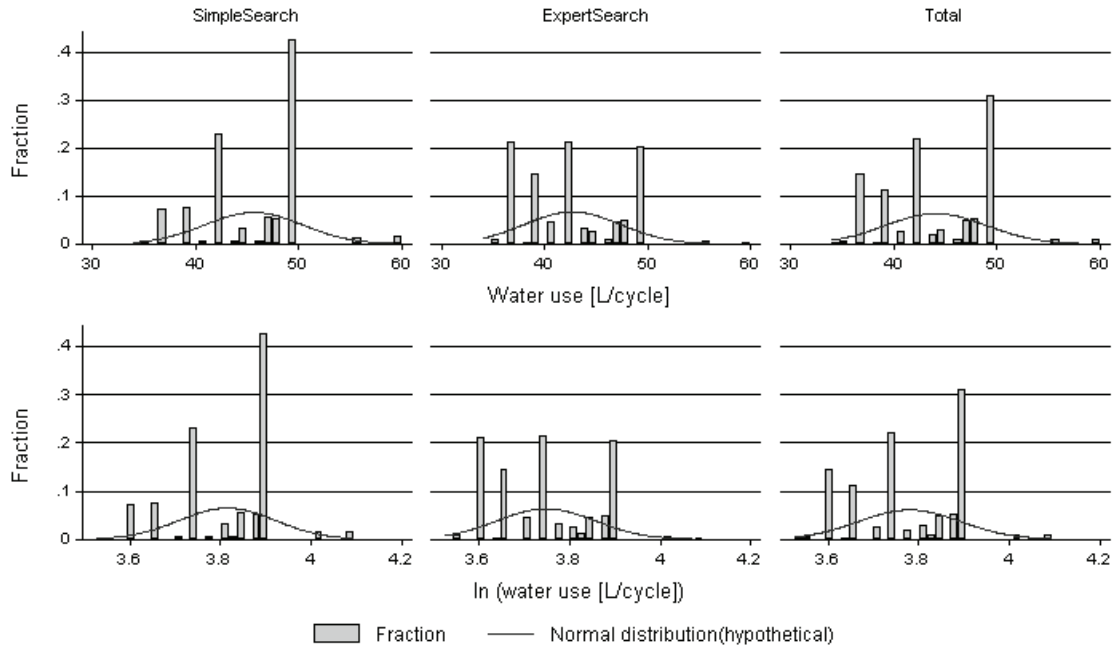
N(total)=2065

Figure 59: Energy efficiency classes by appliance types (online shop round 2)



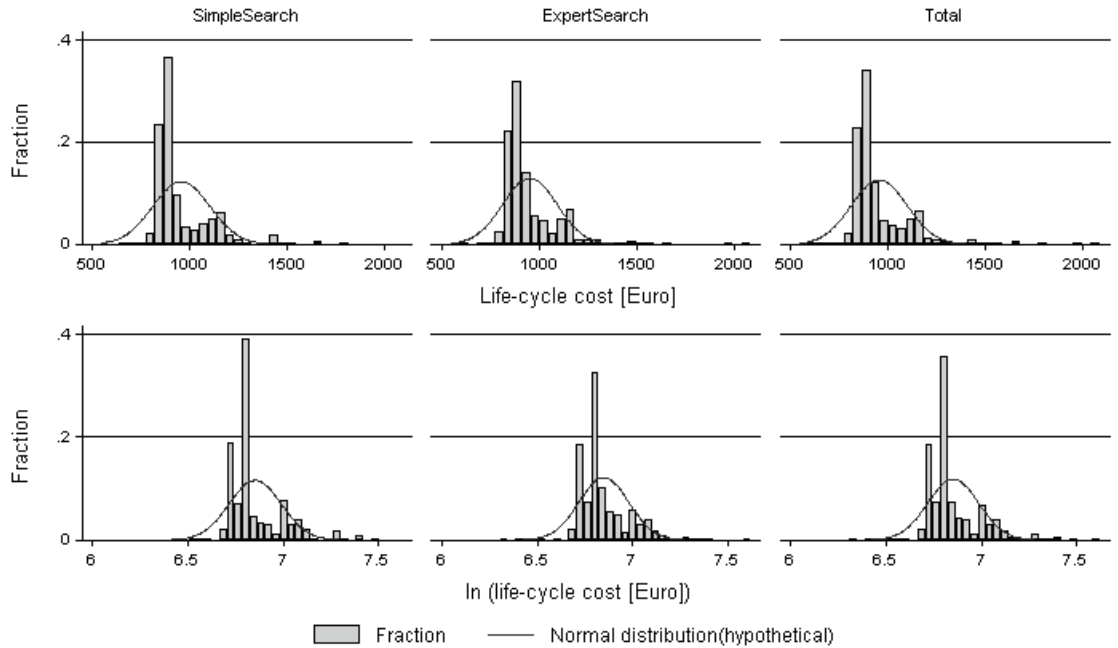
Note: The “A Plus” category did not exist for washing machines as an official EU label at the time of the experiment. It is a supplementary label indicating relatively high energy efficiency and was developed by the retailer himself.

Figure 60: Water use histograms for clicked appliances (online shop round 2)



N(total)=2065

Figure 61: Life-cycle cost histograms for clicked appliances (online shop round 2)



N(total)=2065

Table 119: Price quartiles for clicked appliances (online shop round 2)

	<i>N</i>	<i>Min.</i> price	<i>p25%</i> price	<i>p50%</i> price	<i>p75%</i> price	<i>Max.</i> price
<i>Simple search</i>						
Control	498	299	400	400	500	1160
Treatment	492	299	400	400	550	1160
Total	990	299	400	400	550	1160
<i>Expert search</i>						
Control	542	299	400	480	580	1160
Treatment	533	299	400	480	550	1039
Total	1075	299	400	480	570	1160
<i>Overall</i>						
Control	1040	299	400	449	550	1160
Treatment	1025	299	400	450	550	1160
Total	2065	299	400	450	550	1160

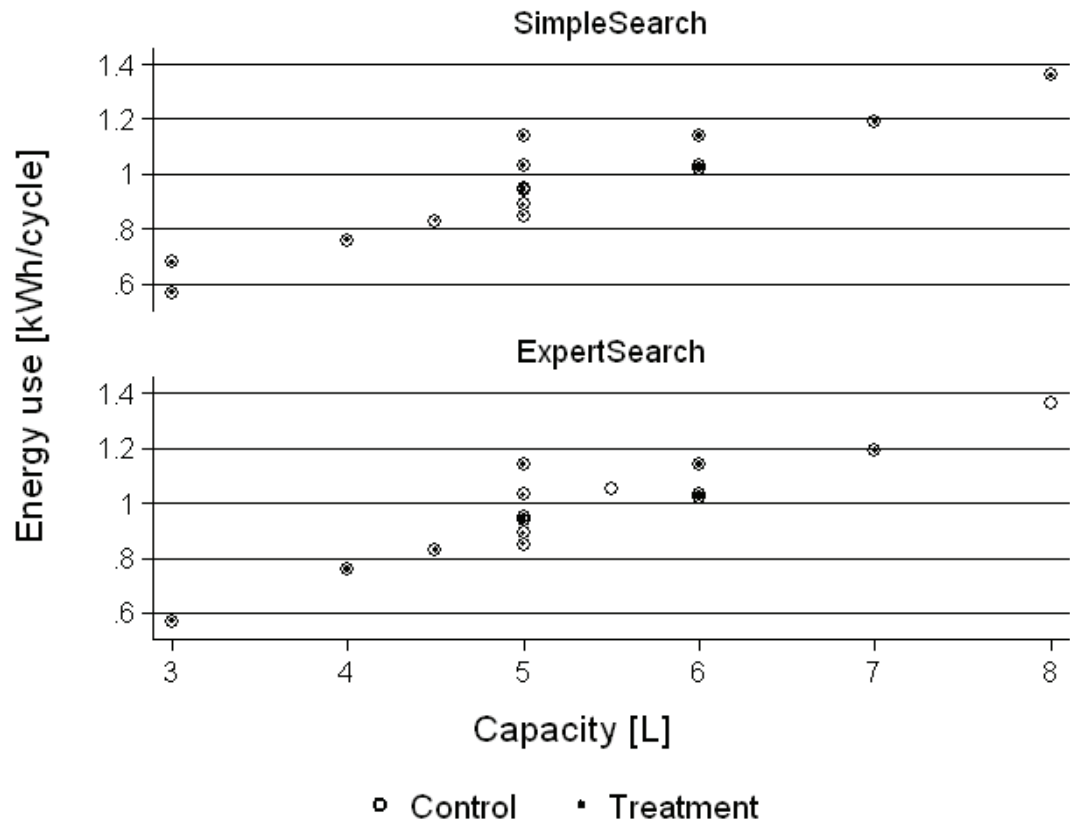
Note: Price in [Euro]

Table 120: Capacity quartiles for clicked appliances (online shop round 2)

	<i>N</i>	<i>Min.</i> capacity	<i>p25%</i> capacity	<i>p50%</i> capacity	<i>p75%</i> capacity	<i>Max.</i> capacity
<i>Simple search</i>						
Control	498	3	5	6	6	8
Treatment	492	3	5	6	6	8
Total	990	3	5	6	6	8
<i>Expert search</i>						
Control	542	3	5	5	6	8
Treatment	533	3	5	5	6	7
Total	1075	3	5	5	6	8
<i>Overall</i>						
Control	1040	3	5	5	6	8
Treatment	1025	3	5	5	6	8
Total	2065	3	5	5	6	8

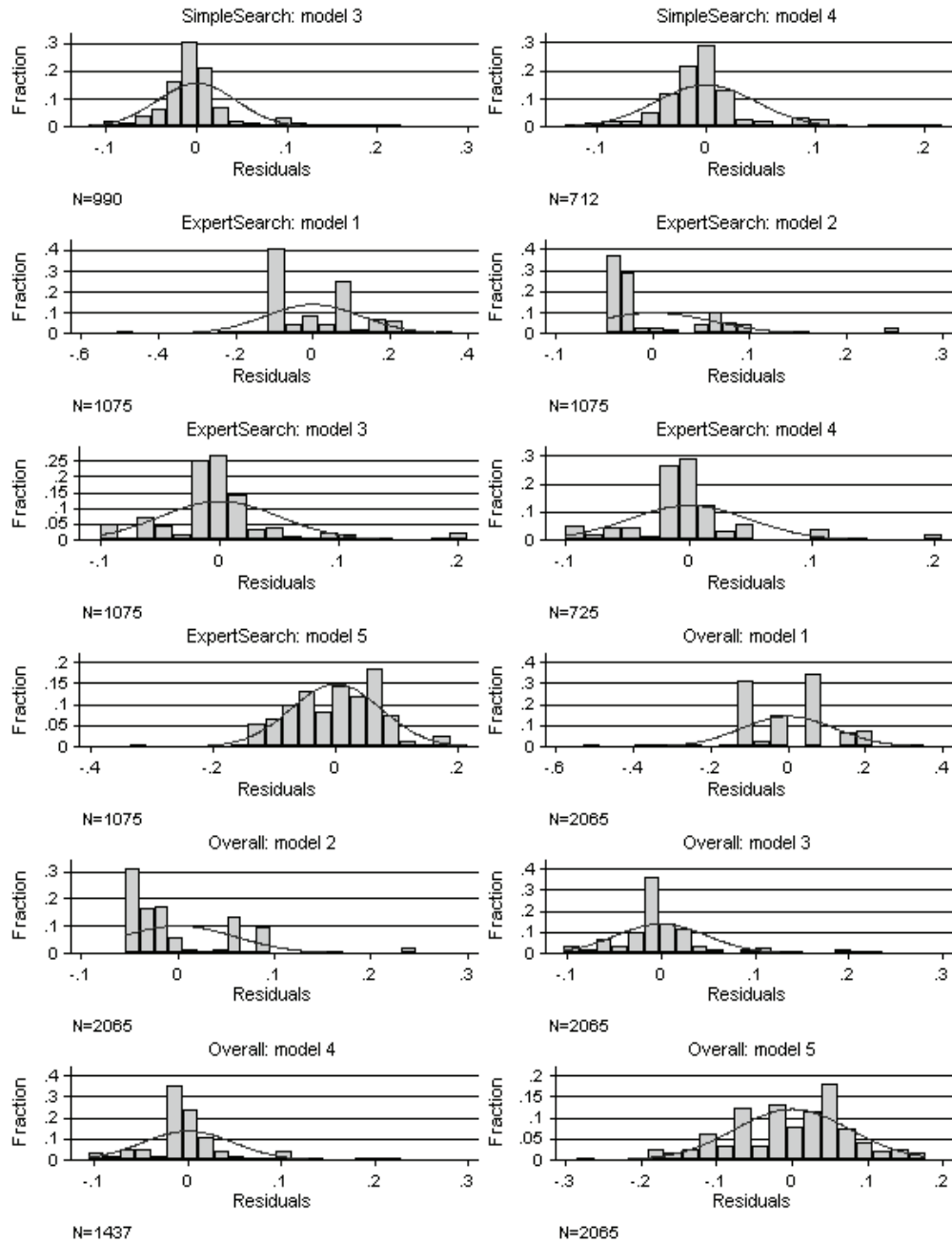
Note: Capacity in [L]

Figure 62: Energy vs. capacity scatter plots by search mode (online shop round 2)



N(total)=2065

Figure 63: Residuals of selected models (online shop round 2)



Note: Residuals of models with significant treatment coefficients.

Table 121: Effect size index f^2 for linear regression models (online shop round 2)

<i>Mode</i>	<i>Model 1</i>	<i>Model 2</i>	<i>Model 3</i>	<i>Model 4</i>	<i>Model 5</i>	<i>Model 6</i>
Simple search			0.0060	0.0076		
Expert search	0.0052	0.0056	0.011	0.0093	0.0043	
Overall	0.0031	0.0043	0.0074	0.0072	0.0024	

Note: Effect sizes only from those models with significant ($p < 0.05$) treatment coefficient(s).
 $f^2 = (R^2_{\text{treatment variables}} - R^2_{\text{no treatment variables}}) / (1 - R^2_{\text{treatment variables}})$. (Cohen 1977, 410-413)

Table 122: Assumed time horizon in the treatment group (online shop round 2)

<i>Assumed time horizon [years]</i>	<i>No adjustment (No. of users)</i>	<i>Adjustment, no click-through (No. of users)</i>	<i>Adjustment and click-through(s) (No. of users)</i>	<i>Total</i>	
.1	0	1	0	1	0.0%
1	0	16	2	18	0.0%
2	0	2	0	2	0.0%
3	0	3	1	4	0.0%
4	0	1	0	1	0.0%
5	0	4	2	6	0.0%
6	0	1	0	1	0.0%
7	0	3	0	3	0.0%
8	0	3	0	3	0.0%
9*	47626	0	0	47626	99.8%
10	0	24	6	30	0.1%
12	0	3	0	3	0.0%
15	0	8	1	9	0.0%
20	0	1	0	1	0.0%
Total	47626	70	12	47708	100.0%

Note: * default time horizon

Table 123: Assumed usage frequency in the treatment group (online shop round 2)

<i>Assumed usage frequency [times per week]</i>	<i>No adjustment</i> (No. of users)	<i>Adjustment, no click-through</i> (No. of users)	<i>Adjustment and click-through(s)</i> (No. of users)	<i>Total</i>	
0.5	0	3	0	3	0.0%
0.7	0	1	0	1	0.0%
1	0	32	5	37	0.1%
1.5	0	4	0	4	0.0%
2	0	34	6	40	0.1%
3*	47519	0	0	47519	99.6%
4	0	29	5	34	0.1%
4.5	0	1	0	1	0.0%
5	0	32	6	38	0.1%
6	0	11	2	13	0.0%
7	0	8	1	9	0.0%
8	0	3	3	6	0.0%
10	0	1	0	1	0.0%
12	0	2	0	2	0.0%
Total	47519	161	28	47708	100.0%

Note: * default usage frequency

Table 124: Robustness check for life-cycle cost (online shop round 2)

	<i>ln(lccost)</i>					
	(1) Ssearch	(2) Ssearch	(3) Esearch	(4) Esearch	(5) Overall	(6) Overall
treatment	-0.0011 (0.0050)	-0.0038 (0.0045)	-0.00059 (0.0062)	-0.0049 (0.0053)	0.00031 (0.0043)	-0.0030 (0.0039)
ln(capacity)	0.41*** (0.041)	0.42*** (0.032)	0.34*** (0.035)	0.31*** (0.032)	0.48*** (0.026)	0.46*** (0.025)
mode					0.034*** (0.0046)	0.033*** (0.0041)
constant	6.43*** (0.091)	6.40*** (0.070)	6.43*** (0.059)	6.49*** (0.054)	6.65*** (0.044)	6.66*** (0.040)
efficiency class	Yes	Yes	Yes	Yes	Yes	Yes
brands	Yes	Yes	Yes	Yes	Yes	Yes
other features	Yes	Yes	Yes	Yes	Yes	Yes
preferences	Yes	Yes	No	No	No	No
adj. R-sq	0.683	0.727	0.408	0.474	0.459	0.504
N	990	990	1075	1075	2065	2065

Note: Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001, models (1), (3), and (5): life-cycle cost based on user-adjusted assumptions (treatment) versus common default assumptions (control); models (2), (4), and (6): life-cycle cost based on common default assumptions for both experimental groups

Table 125: Number of click-throughs per user (online shop round 2)

<i>Total number of click- throughs</i>	<i>Number of users (Control)</i>		<i>Number of users (Treatment)</i>		<i>Total</i>	
0	46937	98.5%	47002	98.5%	93939	98.5%
1	545	1.1%	521	1.1%	1066	1.1%
2	119	0.2%	129	0.3%	248	0.3%
3	40	0.1%	32	0.1%	72	0.1%
4	12	0.0%	10	0.0%	22	0.0%
5	3	0.0%	6	0.0%	9	0.0%
6	5	0.0%	1	0.0%	6	0.0%
7	1	0.0%	2	0.0%	3	0.0%
9	1	0.0%	2	0.0%	3	0.0%
11	0	0.0%	1	0.0%	1	0.0%
12	1	0.0%	0	0.0%	1	0.0%
13	0	0.0%	1	0.0%	1	0.0%
15	1	0.0%	0	0.0%	1	0.0%
16	0	0.0%	1	0.0%	1	0.0%
Total	47665	100.0%	47708	100.0%	95373	100.0%

Pearson chi2(13) = 11.3732 Pr = 0.580

Table 126: Price cross-tabulations for all clicked appliances (online shop round 2)

<i>Price</i>	<i>Control</i>		<i>Treatment</i>		<i>Total</i>	
299	10	1.0%	9	0.9%	19	0.9%
299.95	4	0.4%	4	0.4%	8	0.4%
329.95	14	1.3%	15	1.5%	29	1.4%
349.95	25	2.4%	22	2.1%	47	2.3%
369.95	0	0.0%	2	0.2%	2	0.1%
379.95	12	1.2%	15	1.5%	27	1.3%
399	32	3.1%	24	2.3%	56	2.7%
399.95	385	37.0%	354	34.5%	739	35.8%
419.95	19	1.8%	7	0.7%	26	1.3%
429.95	9	0.9%	21	2.0%	30	1.5%
444	3	0.3%	3	0.3%	6	0.3%
449	9	0.9%	4	0.4%	13	0.6%
449.95	74	7.1%	105	10.2%	179	8.7%
469.95	1	0.1%	1	0.1%	2	0.1%
479.95	16	1.5%	26	2.5%	42	2.0%
499.95	143	13.8%	134	13.1%	277	13.4%
529.95	3	0.3%	4	0.4%	7	0.3%
549.95	46	4.4%	49	4.8%	95	4.6%
559.95	1	0.1%	0	0.0%	1	0.0%
569.95	13	1.3%	11	1.1%	24	1.2%
579.95	38	3.7%	41	4.0%	79	3.8%
599.95	24	2.3%	28	2.7%	52	2.5%
619.95	10	1.0%	9	0.9%	19	0.9%
629.95	20	1.9%	15	1.5%	35	1.7%
649.95	5	0.5%	6	0.6%	11	0.5%
679.95	5	0.5%	2	0.2%	7	0.3%
699.95	35	3.4%	49	4.8%	84	4.1%
729.95	31	3.0%	27	2.6%	58	2.8%
749.95	12	1.2%	5	0.5%	17	0.8%
769.95	8	0.8%	0	0.0%	8	0.4%
799.95	17	1.6%	12	1.2%	29	1.4%
849.95	1	0.1%	3	0.3%	4	0.2%
899.95	5	0.5%	5	0.5%	10	0.5%
949.95	1	0.1%	1	0.1%	2	0.1%
979.95	1	0.1%	0	0.0%	1	0.0%
999.95	0	0.0%	4	0.4%	4	0.2%
1039	1	0.1%	4	0.4%	5	0.2%
1159.95	7	0.7%	4	0.4%	11	0.5%
Total	1040	100.0%	1025	100.0%	2065	100.0%

Pearson $\chi^2(37) = 52.1938$ Pr = 0.050

Appendix IX: Potential reductions in CO₂

Table 127: Potential CO₂ reductions in Germany through life-cycle cost disclosure

	Total sales in Germany [1000]	Scope of application of life-cycle cost disclosure [%]	Mean energy use [kWh/usage] year	Average reduction through life-cycle cost disclosure [%]	Usage frequency of discontinuously working appliances [Usage/month] [Usage/week]	Usage per year [Usage/year]	Reduction in electricity consumption [kWh/year]	CO ₂ emission coefficient for Germany [t CO ₂ /kWh]	Yearly CO ₂ -mitigation potential [t CO ₂ /year]
Washing machines	2838	100	0.969	0.83	12.9	154.8	3.53E+06	5.53E-04	1954
Tumble dryers	1138	100	0.969	0.83	9.7	116.4	1.07E+06	5.53E-04	589
Dishwasher	1742	100	0.969	0.83	3.8	197.6	2.77E+06	5.53E-04	1531
Refrigerators/Fridge-freezers	2884	100	230	2.50			1.66E+07	5.53E-04	9182
Freezers	1088	100	231	2.50			6.28E+06	5.53E-04	3475
Total									16730
Reference year	2002		2006		2002			2003	
Reference	GfK 2005	Assumption: mandatory implementation on labels	Results from this dissertation; assumptions for dryers and dishwashers based on washing machines		Schlomann et al. 2004			DIW 2005	

Note: Order-of-magnitude estimates for potential yearly reductions in CO₂ in Germany that assume constant total sales, a constant effect of life-cycle cost disclosure, constant usage behavior, and constant CO₂ emission coefficients of the German electricity sector.

Bibliography

- AGOF (2006). Berichtsband - Zusammenfassung zur internet facts 2006-I. Frankfurt, Arbeitsgemeinschaft Online Forschung e.V. (AGOF).
- Agricola, A.-C. and W. Ahrens (2005). *Initiative EnergieEffizienz : An information campaign on energy efficiency for private households*. ECEEE Summer Study, European Council for an Energy Efficient Economy, Stockholm.
- AHAM (2006). Comments of AHAM to the FTC on its Appliance Labeling Rule. Washington, DC, Association of Home Appliance Manufacturers.
- Alexandru, A., R. Caponio, et al. (2006). *Informing and educating students and their families about energy efficient appliances*. EEDAL'06: International Energy Efficiency in Domestic Appliances & Lighting Conference '06, London.
- Anderson, C. D. and J. D. Claxton (1982). "Barriers to Consumer Choice of Energy Efficient Products." *Journal of Consumer Research* 9(2): 163.
- Australian Greenhouse Office (2006). "Energyrating. Interactive product list." Retrieved 11 July, 2006, from <http://www.energyrating.gov.au>.
- Babbie, E. R. (2004). The practice of social research. Belmont, CA, Thomson/Wadsworth.
- Banerjee, A. and B. D. Solomon (2003). "Eco-labeling for energy efficiency and sustainability: a meta-evaluation of US programs." *Energy Policy* 31(2): 109-123.
- Bertoldi, P. (1999). *Energy efficient equipment within SAVE: Activities, strategies, success and barriers*. SAVE. For an energy efficient millenium, Graz, Austria, Austrian Energy Agency (EVA).
- BGW (2005a). Abwasserstatistik 2003. Berlin, Bundesverband der deutschen Gas- und Wasserwirtschaft (BGW)

- BGW (2005b). Kurz notiert: Trinkwasserpreise. *BGW-News*. Berlin, Bundesverband der deutschen Gas- und Wasserwirtschaft (BGW)
- Birnbaum, M. H. (2004). "Human Research and Data Collection via the Internet." *Annual Review of Psychology* **55**: 803.
- Bjorner, T. B., L. G. Hansen, et al. (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 T. M. Carter (1971). "Robustness in Regression Analysis." *Sociological Methodology* **3**: 118-146.
- Brewer, G. D. and P. C. Stern (2005). Decision making for the environment : social and behavioral science research priorities. Washington, DC, National Academies Press.
- Buchanan, T. and U.-D. Reips (2001). Platform-dependent biases in Online Research: Do Mac users really think different? Perspectives on Internet research: Concepts and methods [WWW document]. K. J. Jonas, P. Breuer, B. Schauenburg and M. Boos.
- Bundesministerium für Umwelt (2006). Ökoeffiziente Haushaltsgeräte – Innovative Informations- und Vermarktungsstrategien und zeitgemäße Standards. Zusammenfassung. 5. Fachdialog im Rahmen des nationalen Dialogprozesses zur Förderung nachhaltiger Konsum- und Produktionsmuster. Berlin, Bundesministerium für Umwelt, Umweltbundesamt.
- Bush, E., S. Attali, et al. (2006). *Topten.info: Fast selection, best choice*. EEDAL'06: International Energy Efficiency in Domestic Appliances & Lighting Conference '06, London.
- Camerer, C. F. and G. Loewenstein (2004). Behavioral Economics: Past, Present, Future. Advances in Behavioral Economics. C. F. Camerer, G. Loewenstein and M. Rabin. Princeton University Press, Princeton.

- Chiang, K.-P., R. R. Dholakia, et al. (2005). e-search: a conceptual framework of online consumer behavior. Web systems design and online consumer behavior. Y. Gao. Hershey, PA, Idea Group Pub.: 1-18.
- Coase, R. H. (1937). "The Nature of the Firm." *Economica* 4(16): 386-405.
- Cohen, J. (1977). Statistical power analysis for the behavioral sciences. New York, Academic Press.
- DENA (2006). "Initiative Energieeffizienz." Deutsche Energie-Agentur. Retrieved 11 July, 2006, from <http://www.initiative-energieeffizienz.de>.
- 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.
- DIW (2005). Specific CO2 emissions of electricity generation in Germany. Personal Communication with Hans-Joachim Ziesing as of 2005-04-12. Berlin, Deutsches Institut für Wirtschaftsforschung.
- Drèze, X. and F. Zufryden (1998). "Is Internet Advertising Ready for Prime Time?" *Journal of Advertising Research* 38(3): 7-18.
- 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. Newark, University of Delaware.
- du Pont, P., P. Schwengels, et al. (2005). Designing and implementing a labeling program. Energy-efficiency labels and standards: a guidebook for appliances, equipment, and lighting. S. Wiel and J. E. McMahon. Washington, DC, Collaborative Labeling and Appliance Standards Program (CLASP).

- Dyer, R. F. and T. J. Maronick (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 (1994). Commission Directive 94/2/EC of 21 January 1994 implementing Council Directive 92/75/EEC with regard to energy labelling of household electric refrigerators, freezers and their combinations. European Commission, Official Journal of the European Union. L045 17/02/1994: 1-22.
- 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. European Commission, Official Journal of the European Union. L136, 21.6.1995: 1.
- EC (2003). Commission Directive 2003/66/EC as of July 2003 amending Directive 94/2/EC implementing Council Directive 92/75/EEC with regard to energy labelling of household electric refrigerators, freezers and their combinations. European Commission, Official Journal of the European Union. L170 9.7.2003: 10-14.
- Enerdata sa and Fraunhofer ISI (2003). Energy efficiency in the European Union 1990-2001. SAVE-ODYSSEE Project on Energy Efficiency Indicators.
- Ester, P. and R. A. Winett (1982). "Toward More Effective Antecedent Strategies for Environmental Programs." *Journal of Environmental Systems* 11(3): 201-221.
- European Commission (2005a). Doing more with less. Green Paper on energy efficiency. Brussels, European Commission.
- European Commission (2005b, 2005-02-25). "Expansion of pan-European public web database on energy efficient appliances. Project description from the IntelleBase database." Retrieved 2005-08-30, from <http://europa.eu.int/comm/energy/iebase/introduction.cfm>.
- European Commission (2006a). "European Appliance Information System." European Commission. Retrieved 11 July, 2006, from <http://www.eais.info>.

- European Commission (2006b). Report on the Analysis of the Debate of the Green Paper on Energy Efficiency. Commission Staff Working Document. Brussels, European Commission.
- EWI (2005). Energiereport IV: Die Entwicklung der Energiemärkte bis zum Jahr 2030. Energiewirtschaftliche Referenzprognose. Untersuchung im Auftrag des Bundesministeriums für Wirtschaft und Arbeit, Berlin Köln, Basel, Energiewirtschaftliches Institut an der Universität zu Köln, Prognos AG.
- Federal Trade Commission (2006). "Agency Information Collection Activities; Comment Request." *Federal Register* **71**(121): 36088-36096.
- Fisch, M. and C. Gscheidle (2006). "Ergebnisse der ARD/ZDF-Online-Studien 1997 bis 2006." *Media Perspektiven*(8/2006): 431-440.
- Frederick, S., G. Loewenstein, et al. (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.
- Gately, D. (1980). "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables: Comment." *The Bell Journal of Economics* **11**(1): 373-374.
- Gesellschaft für Konsumforschung (2005). E-Commerce-Anteil der Elektrogroßgeräte 2001-2004 auf der Basis des GfK-Haushaltspanels. Persönliche Mitteilung von Göran Seil (Email vom 24.03.2005). Nürnberg.
- 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 R. Selten (2001). Rethinking Rationality. Bounded rationality : the adaptive toolbox. G. Gigerenzer and R. Selten. Cambridge, Mass., MIT Press: 1-12.

- Graulich, K. (2006). *EcoTopTen - Innovations for Sustainable Consumption*. EEDAL'06: International Energy Efficiency in Domestic Appliances & Lighting Conference '06, London.
- Guttman, R. H., A. G. Moukas, et al. (1998). "Agent-mediated electronic commerce: a survey." *Knowledge Engineering Review*. Vol. 13 **13**(2): 147.
- Harrington, L., R. Foster, et al. (2005). *Energy efficiency on the Web - the new frontier*. ECEEE Summer Study, European Council for an Energy Efficient Economy, Stockholm.
- Harrison, G. W. and J. A. List (2004). "Field experiments." *Journal of Economic Literature* **XLII**(December 2004): 1009-1055.
- Hassett, K. A. and G. E. Metcalf (1993). "Energy conservation investment : Do consumers discount the future correctly?" *Energy Policy* **21**(6): 710-716.
- Häubl, G. and V. Trifts (2000). "Consumer decision making in online shopping environments: The effects of interactive decision aids." *Marketing Science* **19**(1): 4.
- Hausman, J. A. (1979). "Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables." *The Bell Journal of Economics* **10**(1): 33-54.
- Hertwig, R. and A. Ortmann (2001). "Experimental practices in economics: A methodological challenge for psychologists?" *Behavioral and Brain Sciences* **24**(03): 383-403.
- Hofacker, C. F. and J. Murphy (2005). Using Server Log Files and Online Experiments to Enhance Internet Marketing. *Contemporary research in e-marketing*. S. Krishnamurthy. Hershey, PA, Idea Group Pub. **1**: 226-249.
- Holland, P. W. (1986). "Statistics and Causal Inference." *Journal of the American Statistical Association* **81**(396): 945-960.
- Howarth, R. B. and A. H. Sanstad (1995). "Discount Rates and Energy Efficiency." *Contemporary Economic Policy* **13**(3): 101.

- Hutton, R. B. and W. L. Wilkie (1980). "Life Cycle Cost: A New Form of Consumer Information." *Journal of Consumer Research* **6**(4): 349-360.
- Jaffe, A. B. and R. N. Stavins (1994). "The energy-efficiency gap. What does it mean?" *Energy Policy* **22**(10): 804-810.
- Jamali, H. R., D. Nicholas, et al. (2005). "The use and users of scholarly e-journals: a review of log analysis studies." *Aslib Proceedings* **57**(6): 554.
- Jungermann, H., H.-R. Pfister, et al. (2005). Die Psychologie der Entscheidung. Eine Einführung. Heidelberg, Spektrum Akademischer Verlag.
- Kahneman, D. and A. Tversky (1979). "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* **47**(2): 263-292.
- Katzev, R. D. and T. R. Johnson (1987). Promoting energy conservation : an analysis of behavioral research. Boulder, Westview Press.
- Kempton, W. and L. Montgomery (1982). "Folk quantification of energy." *Energy* **7**(10): 817-827.
- Kuckartz, U. and A. Rheingans-Heintze (2004). Umweltbewusstsein in Deutschland 2004. Ergebnisse einer repräsentativen Bevölkerungsumfrage für das Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit. Marburg, Bundesministerium für Umwelt, Naturschutz und Reaktorsicherheit.
- Leire, C. and A. Thidell (2005). "Product-related environmental information to guide consumer purchases - a review and analysis of research on perceptions, understanding and use among Nordic consumers." *Journal of Cleaner Production* **13**(10-11): 1061-1070.
- Liebermann, Y. and M. Ungar (1983). "Effects of Inflation on Consumer Choice." *Journal of Business Research* **11**(3): 379-388.
- Liebermann, Y. and M. Ungar (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 E. J. Johnson (2002). "When web pages influence choice: effects of visual primes on experts and novices." *Journal of Consumer Research* **29**(2): 235-245.
- March, J. G. (1994). A primer on decision making : how decisions happen. New York Free Press, Toronto.
- McMahon, J. E., M. McNeil, et al. (2005). Analyzing and setting standards. Energy-efficiency labels and standards: a guidebook for appliances, equipment, and lighting. S. Wiel and J. E. McMahon. Washington, DC, Collaborative Labeling and Appliance Standards Program (CLASP).
- McNeill, D. L. and W. L. Wilkie (1979). "Public Policy and Consumer Information: Impact of the New Energy Labels." *Journal of Consumer Research* **6**(1): 1-11.
- Meier, A. K. and J. Whittier (1983). "Consumer discount rates implied by purchases of energy-efficient refrigerators." *Energy* **8**(12): 957-962.
- Miller, G. (1956). "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information." *The Psychological Review* **63**: 81-97.
- Mills, E. (2004). "Inter-comparison of North American residential energy analysis tools." *Energy and Buildings* **36**(9): 865-880.
- Moe, W. W. (2006). "A field experiment to assess the interruption effect of pop-up promotions." *Journal of Interactive Marketing* **20**(1): 34-44.
- Mullarkey, G. W. (2004). "Internet measurement data - practical and technical issues." *Marketing Intelligence & Planning*(1): 42-58.
- Murphy, J., C. F. Hofacker, et al. (2001). "Website-generated market-research data: Tracing the tracks left behind by visitors." *Cornell Hotel and Restaurant Administration Quarterly; Ithaca* **42**(1): 82.

- MWV (2006). Weekly gas prices for Germany. Personal communication with Roland Lorenz. Email of 17 Oct 2006. Hamburg, Mineralölwirtschaftsverband e.V. (MWV).
- Neter, J. and W. Wasserman (1974). Applied linear statistical models; regression, analysis of variance, and experimental designs. Homewood, Ill., R. D. Irwin.
- Nicholas, D. and P. Huntington (2003). "Micro-Mining and Segmented Log File Analysis: A Method for Enriching the Data Yield from Internet Log Files." *Journal of Information Science* **29**(5): 391-404.
- Nicholas, D., P. Huntington, et al. (2002). "Evaluating metrics for comparing the use of web sites: a case study of two consumer health web sites." *Journal of Information Science* **28**(1): 63-75.
- Niedrig-Energie-Institut (2006). "Spargeräte." Niedrig-Energie-Institut. Retrieved 11 July, 2006, from <http://www.spargeraeete.de>.
- Nielsen/Netratings (2004). Keine wichtige Kaufentscheidung ohne die Nutzung des Internets. Pressemeldung vom 27.01.2004. Nürnberg.
- Norman, K. L. (1991). The psychology of menu selection : designing cognitive control at the human/computer interface. Norwood, N.J., Ablex Pub. Corp.
- Patton, M. Q. (1990). Qualitative Evaluation and Research Methods. Newbury Park, London, New Delhi, Sage.
- Payne, J. W., J. R. Bettman, et al. (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." Quelle GmbH. Retrieved 20 November, 2006, from http://karstadtquelle.de/download/Fact_Sheet_quelle.de_final.pdf.

- Reips, U.-D. (2001). "The Web Experimental Psychology Lab: Five years of data collection on the Internet." *Behavior Research Methods, Instruments & Computers* **3**(2): 201-211(11).
- Reips, U.-D. (2002a). "Internet-Based Psychological Experimenting: Five Dos and Five Don'ts." *Social Science Computer Review* **20**(3): 241-249.
- Reips, U.-D. (2002b). "Standards for Internet-Based Experimenting." *Experimental Psychology* **49**(4): 243-256.
- Rossi, P. H., H. E. Freeman, et al. (1999). Evaluation : a systematic approach. Thousand Oaks, Calif., Sage Publications.
- Rubik, F. and P. Frankl (2005). The future of eco-labelling : making environmental product information systems effective. Sheffield, UK, Greenleaf Pub.
- S.A.F.E. (2005). "topten.ch." Swiss Agency for Efficient Energy Use. Retrieved 8 August, 2005, from <http://www.topten.ch>.
- Sammer, K. and R. Wüstenhagen (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 R. B. Howarth (1994). "'Normal' markets, market imperfections and energy efficiency." *Energy Policy* **22**(10): 811-818.
- Schlomann, B., E. Gruber, 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.
- Scott Morton, M. S. (1984). The state of the art of research. The Information systems research challenge. F. W. McFarlan. Boston, Mass., Harvard Business School Press.

- 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., S. H. Barr, et al. (1988). "Decision support system effectiveness: a review and an empirical test." *Management Science* **34**(2): 139.
- Shippee, G. (1980). "Energy Consumption and Conservation Psychology: A Review and Conceptual Analysis." *Environmental Management* **4**(4): 297.
- Shugan, S. M. (1980). "The Cost of Thinking." *Journal of Consumer Research* **7**(2): 99-111.
- Siderius, H.-P. (2003). *HomeSpeed: a pan-European database, basis for market transformation*. Energy Efficiency in Domestic Appliances and Lighting, Turin, Italy, Softech.
- Simon, H. A. (1955). "A Behavioral Model of Rational Choice." *The Quarterly Journal of Economics* **69**(1): 99-118.
- Simon, H. A. (1957). Models of man: social and rational; mathematical essays on rational human behavior in society setting. New York, Wiley.
- Smith, M. D. and E. Brynjolfsson (2001). "Consumer Decision-Making at an Internet Shopbot: Brand Still Matters." *Journal of Industrial Economics* **49**(4): 541-58.
- Stavins, R. N. (2001, 10-26-2001). "Experience with market-based environmental policy instruments. Prepared for the Handbook of Environmental Economics."
- Stern, M. O. (1978). "Life cycle costing, government policies and the diffusion of energy-conserving technology." *Energy* **3**(2): 173-202.
- Stern, P. C. (1986). "Blind spots in policy analysis: what economics doesn't say about energy use." *Journal of Policy Analysis and Management* **5**(2): 200-227.
- Stern, P. C. (1992). "What psychology knows about energy conservation." *American Psychologist* **47**(10): 1224-1232.

- Stock, J. H. and M. W. Watson (2003). Introduction to econometrics. Boston, MA, Addison Wesley.
- Strüker, J., S. Sackmann, et al. (2004). *Case study on retail customer communication applying ubiquitous computing*. Proceedings of the IEEE International Conference on E-Commerce Technology.
- Sutherland, R. J. (1991). "Market barriers to energy-efficiency investments." *Energy Journal* **12**(3): 15.
- Tan, P.-N. and V. Kumar (2002). "Discovery of Web Robot Sessions Based on their Navigational Patterns." *Data Mining and Knowledge Discovery* **6**: 9-35.
- Thorne, J. and C. Egan (2002). An evaluation of the Federal Trade Commission's EnergyGuide appliance label: final report and recommendations. Washington, DC, American Council for an Energy-Efficient Economy.
- Trochim, W. M. (2004). "The Research Methods Knowledge Base." 2nd Edition. Retrieved 16 August, 2004, from <http://trochim.human.cornell.edu/kb/index.htm>.
- Tversky, A. and D. Kahneman (1981). "The Framing of Decisions and the Psychology of Choice." *Science* **211**(4481): 453-458.
- US EPA (1994). Determinants of Effectiveness for Environmental Certification and Labeling programs. Washington, DC, Abt Associates, Inc.
- US EPA (1998). Environmental Labeling Issues, Policies and Practices Worldwide. Washington, DC, U.S. Environmental Protection Agency.
- van Eimeren, B. and B. Frees (2006). "ARD/ZDF-Online-Studie 2006. Schnelle Zugänge, neue Anwendungen, neue Nutzer?" *Media Perspektiven*(8/2006): 402-415.
- van Eimeren, B., H. Gerhard, et al. (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.
- Watson, R. T. (2001). Climate change 2001 : synthesis report : contribution of Working Groups I, II, and III to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, Published for the Intergovernmental Panel on Climate Change Cambridge University Press.
- Wiel, S. (2005). Energie-efficiency labels and standards: an overview. Energy-efficiency labels and standards: a guidebook for appliances, equipment, and lighting. S. Wiel and J. E. McMahon. Washington, DC, Collaborative Labeling and Appliance Standards Program (CLASP): 8-39.
- Wilbanks, T. J. and P. C. Stern (2002). New tools for environmental protection: what we know and need to know. New tools for environmental protection : education, information, and voluntary measures. P. C. Stern, T. Dietz and National Research Council (U.S.). Committee on the Human Dimensions of Global Change. Washington, DC, National Academy Press.
- Williamson, O. E. (1975). Markets and hierarchies, analysis and antitrust implications : a study in the economics of internal organization. New York, Free Press.