Relative Performance Transparency: Effects on Sustainable Purchase and Consumption Behavior

by

Shwetha Paramananda Mariadassou

B.A., University of California Los Angeles (2012)

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Author . . . .
Sloan School of Management
May 18, 2017

Certified by . . . .
Yanchong (Karen) Zheng
Assistant Professor of Operations Management
Thesis Supervisor

Accepted by . . . .
Dimitris Bertsimas
Boeing Professor of Operations Research
Co-Director, Operations Research Center

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Abstract

We build on existing operations and marketing research focusing on the effect of information transparency on consumers by studying how transparency into the levels and changes of relative sustainability performance affects consumer behavior. Our work considers two forms of transparency: *process transparency* and *customer transparency*. We operationalize process transparency, in which information about the company's sustainability performance relative to competitors is revealed to the customer, in the product purchase domain. We operationalize customer transparency, in which the customer receives information about their own sustainability performance relative to other customers, in the energy consumption domain. In a series of online consumer choice experiments, we find that within the product purchase domain, transparency into the company's current levels of sustainability performance has a more powerful effect on influencing consumer purchase behavior than transparency into the company's changes in relative sustainability performance over time. Conversely, in the energy consumption domain, we find that transparency into the customer's changes in sustainability performance over time, relative to other customers, has a more dominant effect in motivating energy conservation than transparency into the customer's relative levels of sustainability performance. We employ structural equation models to identify the underlying mechanisms that drive these results.

Thesis Supervisor: Yanchong (Karen) Zheng
Assistant Professor of Operations Management

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Chapter 1

Introduction

In recent years, environmental responsibility has emerged as a leading issue in the public and private sectors, and businesses have benefited from revealing their support for the cause. During the 2010 World Cup, Nike's national teams wore jerseys made from recycled plastic bottles, promoting Nike's environmentally conscious image on a global scale [42]. On Black Friday in 2011, Patagonia ran an ad in the New York Times titled "Don't Buy This Jacket," which reported the environmental costs of producing one jacket and encouraged consumers to "buy less and reflect" in the face of diminishing environmental resources [37]. Their subsequent sales rose. Governments encourage consumers to be conscious of their carbon footprint at an individual level by incentivizing fuel-efficient vehicles through tax credits and carpool lane stickers.

As the issue of environmental responsibility grows in increasing importance, corporations must determine the amount of effort to expend in pursuing sustainable practices and also the appropriate way in which to convey their efforts and their results to their consumers [28, 45]. We build on existing operations and marketing research focusing on the effect of information transparency on consumers [16, 24, 28] by studying how transparency into the levels and changes of relative sustainability performance affects purchase and consumption behavior. Our work considers two forms of transparency, one in which information about the company's processes is revealed to the customer (process transparency) and the other in which information about the customers is revealed to the customer (customer transparency). While both have been studied extensively, we offer a comparison of the two, particularly within the domain of sustainability. We operationalize process transparency in the product purchase domain and customer transparency in the energy consumption domain. We propose that both types of transparency are effective in motivating behavioral change yet may operate through different mechanisms.

Within these types of transparency, we define transparency into *levels* as revealing current performance at a given point in time; conversely, transparency into *changes* refers to revealing of change in performance over a time period. We address the following key research questions: (i) How does transparency into a company's sustainability performance, relative to its competitors, affect customer purchase behavior? (ii) How does transparency into a customer's sustainability performance, relative to other customers, affect customer consumption behavior? (iii) Does transparency in current performance level or transparency in the change of performance have a more significant impact on behavior? (iv) What underlying mechanisms drive these effects?

Chapter 2

Transparency

We consider transparency in two different realms: the type of transparency (process or customer) and the dimension revealed (levels or changes). While the literature comparing the revelation of *levels* versus *changes* is sparse, there exists much literature regarding transparency type.

2.1 Process Transparency: Revealing Company Processes to Customers

Transparency into a company has been shown to improve consumers' trust in a company and their perception of a company's service value [9, 10, 59]; in many instances, this results in a higher likelihood of a customer purchasing a product by this company. Revealing the effort involved in delivering the final product can result in increased gratitude, which translates into increased willingness to pay and overall satisfaction [40]. Furthermore, the time and effort in the production process can serve as a heuristic for product quality [13, 32]. On the other hand, there is an inherent risk in transparency that exposing undesirable information to a customer will result in dissatisfaction towards the company [46]. Given the tradeoff, companies must decide the extent to which they choose to be transparent and the information that they convey.

In additional to general transparency, there is a growing body of literature surrounding transparency that reveals a worthy cause. Research has shown that cause-related marketing can positively impact consumers' purchase behavior [3, 31, 34, 47]. For example, [31] find that when a firm links one of their products to a particular cause, the spillover effect is strong enough that the firm can raise prices on multiple products, increasing overall profit. With respect to transparency surrounding worthy causes, [24] conduct a field experiment in which they find increased demand and lower price elasticity when coffee has a fair trade label. Possible motives include intrinsic motives of pure altruism or impure altruism, reputation concerns, or perceived product quality. In another instance, [30] find that consumers are willing to pay more for a product when a company enhances visibility into its social responsibility practices, with indirect reciprocal motives– in which consumers reward firms' actions towards a third party– playing a role.

Our work focuses on transparency within the realm of environmental responsibility. Within this realm, researchers have explored the type and manner in which information presented impacts behavior. [41] reveal that the order in which energy-efficient practices are recommended affects the likelihood that small and medium firms adopt these practices. Other studies have shown the value of something as small as transparency through eco-labels in positively influencing consumers, whether it be dolphin-safe labels that increase market share [56], shade-grown labels in coffee production that promote environmentally sound harvesting practices [35], fair-trade coffee labels resulting in higher satisfaction with taste [53], or even in eco-labelled lamps enhancing task performance [52]. In fact, even transparency into negative environmental practices may benefit a company. [28] find that voluntary disclosure of a high level of greenhouse gas emissions can actually increase market share if competitors do not disclose information. If competitors do subsequently reveal a low emissions level, the original firm is still favored due to its leadership in being the first to voluntarily disclose this information. Other research has shown that voluntary disclosures about poor performance increase trust [25], which subsequently can lead to brand loyalty and increased market share [12].

2.2 Customer Transparency: Revealing Customer Behavior to Customers

The second type of transparency we consider is revealing customers' behavior. This idea of influencing behavior by telling people about their peers' behavior is known as the "social norm approach" [11]. This approach has been applied in a number of different settings, including voting, retirement savings, charitable giving, and alcohol consumption in colleges [20, 21, 1, 11, 6]. Presenting social norms can influence behavior for a number of reasons. First, social norms can offer informational influence; people are presented with additional information that offers evidence about reality and affects how these individuals determine their personal payoffs.

Second, they are influenced by social norms and peer pressure because they feel the urge to socially conform [17].

We consider a specific type of customer transparency, in which a customer is shown his or her own performance relative to the performance of other people. Studies have shown that this relative performance feedback (particularly when public) is effective in altering behavior, likely a result of the additional reputation concerns that are introduced [16, 51]. However, this behavior can vary widely. In some instances, presenting peer information can result in shifting behavior away from the desired result. As evidenced by the phenomenon termed "the boomerang effect," people may not want to deviate from descriptive peer norms that they are shown. This means that many people tend to adjust behavior towards the norm, even if their initial performance is more desirable than the norm behavior [50]. Additionally, disseminating peer information may generate an oppositional reaction, in which people shift behavior even further away from the norm, perhaps due to discouragement from social comparisons [6]. On the other hand, individuals may exhibit a certain type of behavior (ahead-seeking, behind-averse behavior, or last-place aversion) that shifts behavior in the favorable direction [48, 33].

Within environmental sustainability, the effectiveness of the social norms approach has been seen in a number of contexts: towel reuse, water conservation efforts, food waste, and energy consumption [22, 19, 44, 50, 43, 5, 1]. Our search builds on the energy consumption cases. The motivations to conserve include intrinsic motivations, extrinsic motivations, and reputation or image motivations [16]. The importance of intrinsic motivations was illustrated in a field experiment in Los Angeles that also highlighted the importance of framing effects [4]. The authors found that portraying consumption as a health-based community concern yields more of a long-term impact than when framed solely as a cost-based concern, the latter being a more extrinsic motivation. The power of image motivations was illustrated by a study in the UCLA dorms, which showed that public information was particularly effective for reducing energy consumption [16]. In the energy consumption cases, there is mixed evidence regarding the "boomerang effect" [50, 5]. [50] suggest that it is mitigated when information is disseminated in conjunction with an injunctive component that conveys the typically approved behavior; however, [5] still see evidence of the "boomerang effect" in the large scale oPower experiments that were conducted. At the very least, there is certainly heterogeneity in subsequent energy reduction based on pre-treatment levels of consumption, with higher pre-treatment households reducing at a larger rate [5, 1]. Based on this information, energy companies must consider how and what type of information to disseminate to customers.

2.3 Research Contribution

While much literature emphasizes the impact of transparency, to our knowledge, we are the first to investigate the impact of revealing relative performance along two dimensions of performance, *levels* and *changes*, and with respect to two types of transparency, transparency about the company's processes and transparency about the customers. *Levels* refers to the performance of an entity at a static point in time. *Changes* refers to the change in performance over time. We operationalize transparency about the company's processes in the purchase domain, through a study in which companies disclose to their customer the company's carbon dioxide emissions relative to the industry. We operationalize transparency about the customer in the energy consumption domain, through a study in which an energy company discloses the customer's energy consumption relative to the consumption of other customers in their neighborhood. This research contributes to sustainable operations management and consumer behavior in two ways.

First, we investigate how process transparency, by revealing carbon dioxide emissions, affects customers' purchase intention and attitude towards the company. We observe that within the purchase domain, transparency in *levels* has a more dominant effect on impacting consumer behavior than transparency in *changes*. From our first study, the average purchase intention in the control treatment (who receives no transparency) is significantly lower than the average purchase intentions in the treatments in which the company fares better than the industry and reveals only that dimension to the customer. Our second study reveals that in nearly all instances in which the company fares better than the industry in *levels*, the average purchase intention is significantly higher than that of the control group, regardless of how the company fares compared to the industry with respect to *changes*. We find that transparency into *levels* operates through three mechanisms. Revealing better performance than the industry benchmark increases positive feelings about oneself, trust in the company, and perceived quality of the product, relative to no transparency.

Second, we investigate how customer transparency, by revealing the customer's energy consumption relative to other customers, affects customers' likelihood to conserve energy in subsequent periods. In sharp contrast to the purchase domain, we observe that transparency in *changes* has a more dominant effect on motivating energy-saving behavior than transparency in *levels*. In nearly all instances in which the household performs worse than its neighbors in *changes*, the average likelihood to reduce consumption in the subsequent month is significantly higher than that of the control group, regardless of how the household fares compared to the neighborhood with respect to *levels*. We see the strongest motivation to conserve energy when participants are shown that they fare worse in both *changes* and *levels*. Given the difficulty in determining the optimal amount of information to convey to consumers [8], these findings offer insight into the types of information that should be conveyed under different circumstances and in turn offer an easily implementable way to influence behavior with limited cost.

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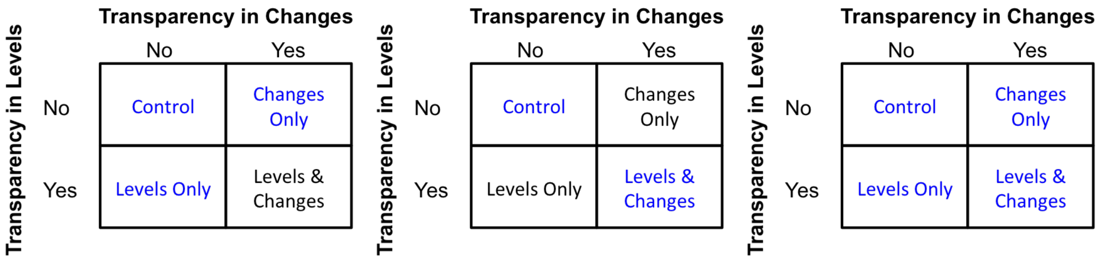
Chapter 3

Experiments

We conduct a series of studies using the Amazon Mechanical Turk platform in which we vary the type and amount of information shown to participants and analyze the effects on behavior. We conduct the studies in two domains, product purchase (Studies 1a and 1b) and energy consumption (Study 2). For all studies, participants were required to be adults residing in the United States and were required to have at least a 95% approval rate on Amazon Mechanical Turk. For Studies 1a and 1b, we required that each participant had successfully completed at least 1,000 tasks on Amazon Mechanical Turk; for Study 2, we required that each participant had successfully completed at least 500 tasks in order to expand our population. In each study, we excluded participants who had completed any of our previous studies. To ensure the quality of the data, we required that participants correctly answer a few attention check questions. In revealing information about performance, we treat performance as having two dimensions: *levels*, which represents a static measure at a given point in time; and *changes*, which represents the difference in the measure over two periods of time. Thus, each study is a variation of a 2 (transparency in levels: yes or no) x 2 (transparency in changes: yes or no) design with four possible treatment groups: *control*, *levels only*, *changes only*, and both *levels and changes*. From left to right, Figure 3.1 illustrates the variations used for Studies 1a, 1b, and 2, with the cells in blue reflecting those treatment groups that were activated for that study. In the product purchase domain, we conduct two studies in which companies disclose their current levels of carbon dioxide (CO_2) emissions or changes in CO_2 emissions as compared to the industry average. We demonstrate that transparency in *levels* has a more dominant effect on purchase intention than transparency in *changes* (Study 1b). By exploring the underlying mechanisms for this behavior, we find that transparency affects positive feelings about oneself, trust in the company, and perceived quality of the product (Study 1a). In the energy consumption domain, we test the effects of disclosing households' current levels of energy consumption or change in energy consumption from the prior month compared to their neighbors' corresponding average value. We find that transparency in *changes* has a more dominant effect on willingness to reduce energy consumption than transparency in *levels*, with primary mechanisms being negative feelings towards oneself, the importance of saving money, and feeling valued by others (Study 2).

Figure 3.1: Study Design



In Study 1a, participants either saw levels only, changes only, or no transparency (*control*). In Study 1b, participants either saw levels and changes or no transparency (*control*). In Study 2, participants either saw levels only, changes only, levels and changes, or no transparency (*control*). Studies 1a and 1b were conducted within the product purchase domain. Study 2 was conducted in the energy consumption domain.

3.1 Process Transparency and Consumer Purchases: Revealing Levels versus Changes in Relative Performance

In Study 1a, we had one control group and two treatment groups, implementing three cells from the aforementioned 2 x 2 design: *control*, *levels only*, and *changes only*. This offers a clean comparison between the impact of transparency in *levels* and the impact of transparency in *changes*. We explore how transparency into a company's sustainability performance influences consumer purchase behavior, building on the research of marketing sustainable products and encouraging consumers to be more environmentally responsible [28, 45, 56]. We then employ structural equation models to identify the mechanisms through which each type of transparency operates.

3.1.1 Participants.

We had 400 participants (60.8% male, mean age (M_{age})= 34.94, standard deviation of age (SD) = 10.38) complete Study 1a for \$1.00. Participants were asked to assume the role of a potential buyer and answer questions relating to a hypothetical purchase scenario. We chose printing paper as the product as it is an inexpensive product with low brand loyalty. All participants saw the image and specifications of one of two brands of printing paper. In addition, the two treatment groups, *levels* and *changes*, were shown charts that illustrated either the company's current level of CO2 emissions compared to the current industry average or the change in the company's CO2 emissions between two periods compared to the average change of the industry (Figure 3.2). All participants were then asked a series of questions about their purchase intentions. We included a question that served as an attention check, in which participants were required to select "somewhat agree" as the answer to the question. We only used data from participants who correctly answered the attention check question in our analysis (N=396, 60.6% male, $M_{age} = 35.0$, $SD = 10.40$).

3.1.2 Design and Procedure.

In the first study, the 400 participants were randomly assigned to either the *control* group or one of two treatment groups, *levels* or *changes*. The *control* group was not shown any transparency beyond the image and specifications of the product. Within the *levels* treatment group, approximately half of the participants were in the *levels better* subgroup. They were shown a chart depicting the total amount of the company's CO2 emissions (in tons of carbon dioxide emitted per ton of production) at a level of 0.671, which is lower than the industry average value of 0.709. The other half were in the *levels worse* subgroup and were shown a chart depicting the same industry average as the *levels better* subgroup (0.709); however, the company level was now higher than the industry average at 0.739 (Figure 3.2). Similarly, within the *changes* treatment group, the two subgroups were shown a chart depicting the percentage change in the company's CO2 emissions since 2010. The *changes better* subgroup was shown the average industry reduction in greenhouse gas emissions to be 4.40%, a smaller percentage than the company's reduction in emissions of 6.64%; conversely, the *changes worse* subgroup saw that the company was reducing emissions more slowly than the industry on average, at 2.93%. The exact values used in all charts were based on sustainability reports from the American Forest & Paper Association to ensure credibility. We used two brands for all treatments while retaining the same chart values to control for potential effects of the brand name on participants' behavior. We designed all charts to be bar charts with a common scale and included the presence of gridlines and tick marks to aid with interpretability [14, 27].

Figure 3.2: Study 1a Images

The left image was shown to the *levels worse* subgroup. The right image was shown to the *changes better* subgroup. Within a performance dimension *levels* or *changes*, the industry average stayed constant while the brand value took one of two values, either better or worse than the average.

3.1.3 Dependent Measures.

Participants indicated their purchase intention by responding to the item: "How likely are you to purchase this product?" (7-point Likert scale; 1 = Very Unlikely to 7 = Very Likely). To measure possible mechanisms, we used questions derived from other studies (See Appendix). We tested whether the effect of transparency on purchase intention is mediated by perceptions of price fairness [7, 39] and product quality [40] by asking participants: "How fair do you think the price of $14.55 is for this product?" and "What is your perceived quality of this product?" We also investigated whether customer perceptions of the company are affected, which are indicative of future purchase intentions and loyalty [38]. We measured customer perceptions of the company using the following questions: "My feelings towards this company can best be described as (very dissatisfied to very satisfied)," "Compared to competitors, this company has a (below average to above average) reputation," "My overall trust in the company is (very low to very high)," and "This company appears more trustworthy than others from which I've purchased" (strongly disagree to strongly agree) [39]. We considered each question individually in our analysis as single-item measures are often as accurate as multi-item scales [58]. In order to investigate attributed motives to the company as a possible mechanism for purchase intention, we asked participants the extent to which they agree with the following statement: "This company feels morally obligated to be environmentally responsible." [29, 18].

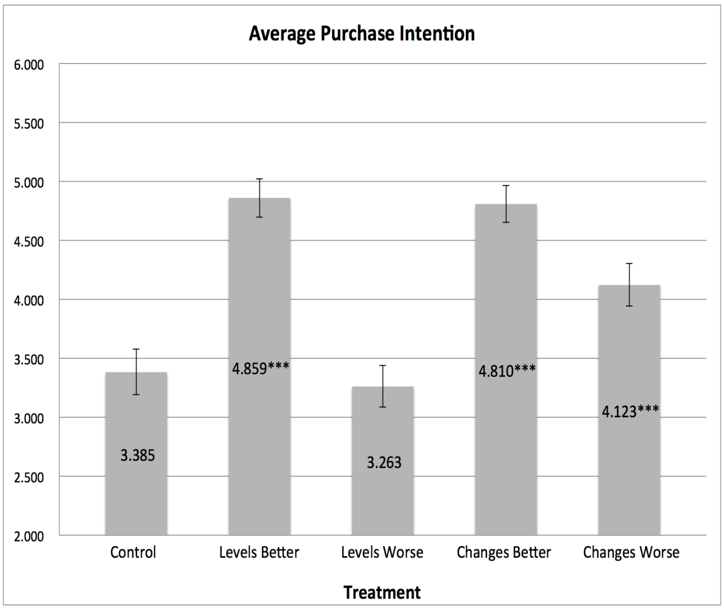
In addition to customer perceptions about the company, we investigated whether customer perceptions of themselves are affected, as positive self-perceptions could result in higher purchase intention. To detect the warm-glow motive, in which customers derive an egoistic benefit from supporting a worthy cause, we ask participants the extent to which they agree with the statement: "I would feel good if I bought this product" [29]. We also asked customers how they perceived their reputation to be affected: "I would enhance my reputation if I bought this product" [29]. Finally, given that the specific cause at hand could have influenced purchase behavior, we asked questions to elicit the pariticipants' cause involvement, or the degree to which they consider this issue personally relevant [23]. We measured cause involvement using an adapted three-item scale, with a high Cronbach's alpha value ($\alpha = 0.9$) [54]: "The issue of carbon dixoide is important to me," "Carbon dioxide emissions directly impact my life," and "The issue of carbon dioxide emissions directly impacts my purchase decisions" [29].

3.1.4 Results and Analysis.

A Wilcoxon rank sum test shows that there was a significant difference in the purchase intention between the *control* group (mean(M)=3.385, standard deviation(SD)=1.700) and the treatment conditions. We found that nearly all types of transparency resulted in a significantly higher purchase intention than the control. Because no significant brand effects were found, we pooled the results from the two brands. Unsurprisingly, when the brand fared better than the industry, we saw the highest values of purchase intention. Using the Likert-type scale to measure purchase intention, the average purchase intention in the *control* group was lower than the average for the treatment group who saw the brand fare better than the industry in *levels* ($M = 4.859$, $SD = 1.430$, $W = 4526$, $p < 0.001$) and the average for the treatment group who saw the brand far better than the industry in *changes* ($M = 4.810$, $SD = 1.397$, $W = 4519$, $p < 0.001$) (Figure 3.3). When the brand fared worse than the industry in changes, the purchase intention was still significantly higher than the control group ($M = 4.123$, $SD = 1.623$, $W = 3922.5$, $p = 0.007$). There was no significant difference between the *control* group and the group that was shown the chart in which the brand fared worse than the industry in *levels* ($M = 3.263$, $SD = 1.581$), suggesting that in no condition did transparency result in a negative effect on purchase intention. This result is consistent with prior research [28], which has shown that transparency that reveals unfavorable performance, even if not necessarily helpful, does not necessarily undermine consumer sentiment.

To explore the mechanisms for the observed behavior, we used structural equation models to conduct a path analysis. From this study, we find that transparency into *levels* affects participants' positive feelings about themselves, their trust in the company, and the perceived quality of the product, relative to no transparency (Figure 3.4). Within *levels*, revealing better performance compared to the industry average is positively associated with positive feelings about oneself ($\beta = 1.128$, $p < 0.001$), trust in the company ($\beta = 0.628$, $p < 0.001$), and perceived quality of the product ($\beta = 0.359$, $p = 0.048$). Conversely, revealing worse performance compared to the industry average is negatively associated with all three measures, relative to no transparency. Feeling good about oneself and trust in the company are strong drivers of purchase intention ($\beta = 0.596$, $p < 0.001$ and ($\beta = 0.189$, $p = 0.008$), respectively) while perceived quality of the product is a marginal driver of purchase intention ($\beta = 0.131$, $p = 0.061$). We note that this model indicates partial mediation. After controlling for feelings about oneself, trust in company, and perceived product quality, transparency that reveals levels of performance

Figure 3.3: Average Purchase Intention



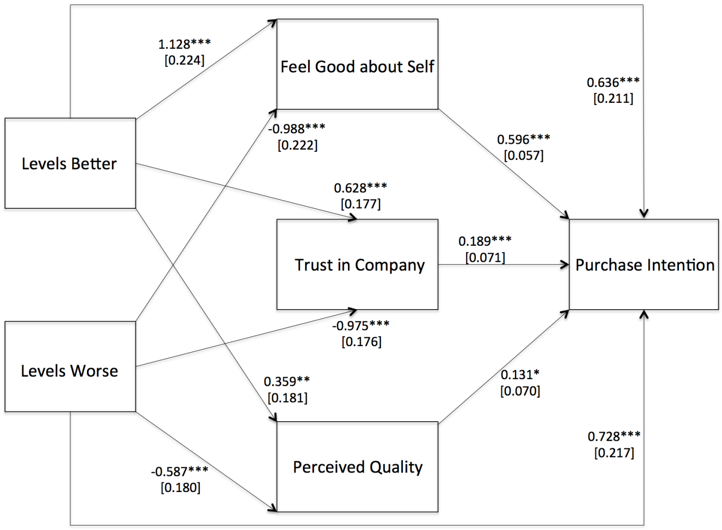
When the brand fared better than the industry average in *levels* or in *changes*, we observed a significantly higher purchase intention than the control ($p < 0.001$). When the brand fared worse than the industry average in *changes*, we still observed a significantly higher purchase intention than the control ($p = 0.007$). There was no significant difference when participants were shown the chart in which the brand fared worse than the industry in *levels*. In no condition did transparency negatively affect purchase intention. Standard error bars are included. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

that are superior or inferior to industry benchmarks still has a positive effect on purchase intentions. The model exhibits a reasonable fit, with a reasonable comparative fit index (CFI) (0.759) and root mean squared error of approximation (RMSEA) (0.384) ($p < 0.01$) (Figure 3.4) but suggests that further analysis must be done to identify more possible mechanisms.

Within *changes*, revealing better performance compared to the industry average is positively associated with positive feelings about oneself ($\beta = 0.589$, $p = 0.005$) and trust in the company ($\beta = 0.496$, $p = 0.002$). Revealing worse performance compared to the industry average is marginally negatively associated with perceived quality of the product ($\beta = -0.392$, $p = 0.016$). Feeling good about oneself, trust in the company, and perceived quality of the product are all significant drivers of purchase intention ($p < 0.001$, $p = 0.007$, and $p < 0.001$, respectively). As with the previous model, this model indicates partial mediation. After controlling for feelings about oneself, trust in company, and perceived product quality, transparency that reveals changes of performance still has a positive effect on purchase intentions. The model exhibits a reasonable fit (CFI (0.470) and RMSEA (0.390) ($p < 0.01$)) (Figure 3.5) but could also benefit from further analysis.

In both dimensions, given that feeling positively about oneself is so strongly related to

Figure 3.4: Study 1a Path Analysis: Levels



Beta coefficients are displayed for the *levels* transparency in Study 1a. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are presented in brackets. We observe feeling good about oneself, trust in the company, and perceived product quality to be mechanisms for increased purchase intention when transparent about levels.

transparency and purchase intention, our results validate the notion of the warm-glow motive [2, 3], in which the benefits derived from the action make the individual feel good about himself.

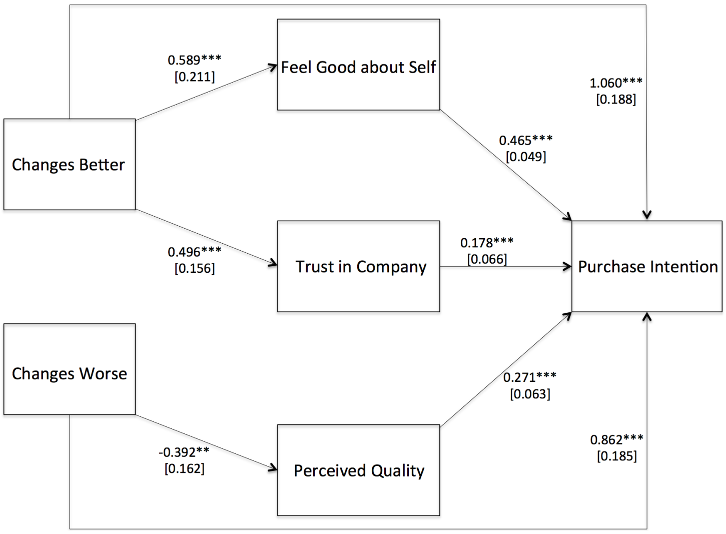
3.2 Process Transparency and Consumer Purchases: Comparing the Effects of Levels versus Changes in Relative Performance

In Study 1b, we had one control group and one treatment group, implementing two cells from the 2 x 2 design: *control* and *levels and changes*. This allows us to determine which dimension of relative performance transparency dominates in this domain.

3.2.1 Participants.

In this related study, we had 2,000 participants (54.7% male, M_{age} = 34.9, SD = 11.20) complete this study for 50 cents. 95% of the participants were in the *levels and changes* group and shown both *levels* and *changes*, while the remaining 5% of participants were in the *control* group and not shown any transparency. We used a large number of participants in the treatment group so that we could map out behavioral differences among varying performances in the *levels* and *changes* dimensions compared to the control. No participants from Study 1a were eligible for Study 1b. We used data from the participants who correctly answered two questions that

Figure 3.5: Study 1a Path Analysis: Changes



Beta coefficients are displayed for the *changes* transparency in Study 1a. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are presented in brackets. While revealing better performance is positively associated with customers feeling good about themselves and their trust in the company, revealing worse performance is negatively associated with perceived product quality. However, revealing worse performance still results in a higher purchase intention.

served as attention checks in our analysis (N=1,914, 54.9% male, M_{age} = 34.8, SD = 11.16). The first attention check was identical to the one used in Study 1a. The second attention check question asked participants what product they saw in this survey and had them select from three choices (T-shirts, laundry detergent, and paper), with "paper" being the correct answer.

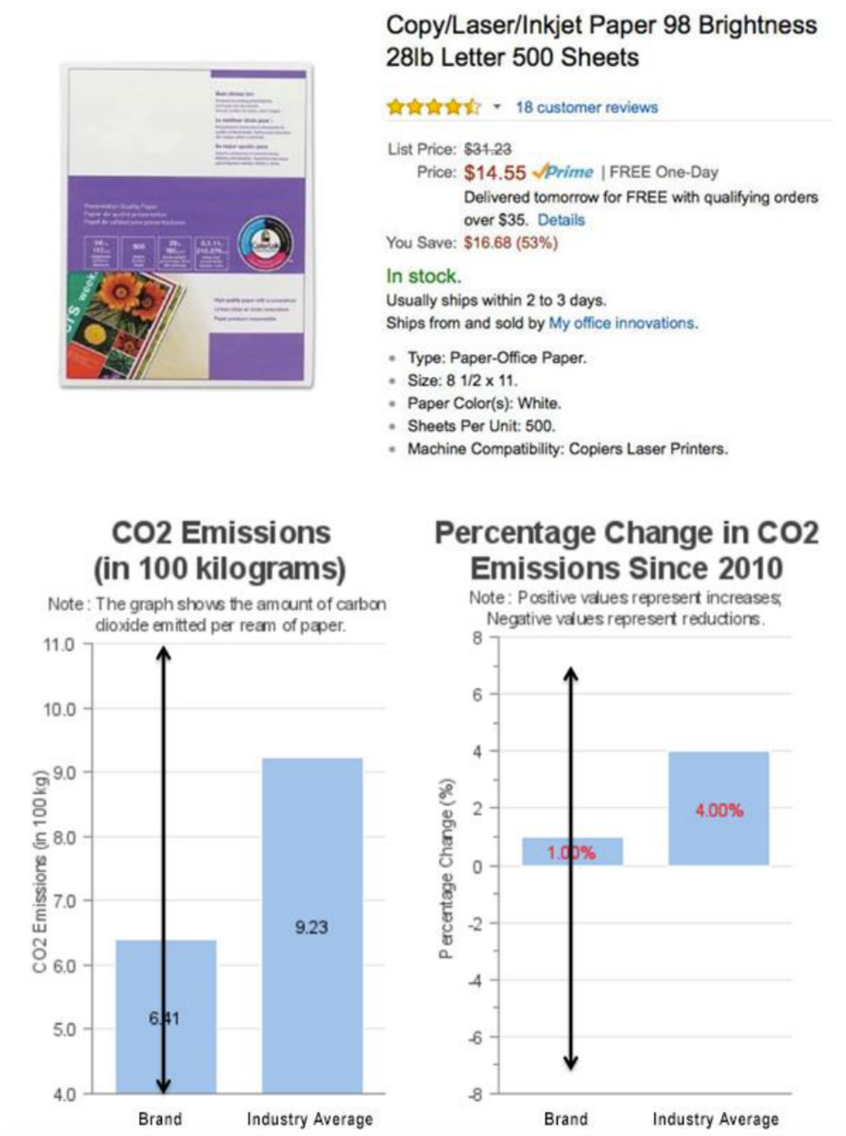
3.2.2 Design and Procedure.

In Study 1b, all participants were again shown the image and specifications of one of two brands of paper. The participants in the *levels and changes* group were each shown a value of the company's current level of CO2 emissions compared to the industry average. The value that each participant was shown for the company's current level of emissions was randomized on a continuous scale between 4.00 and 10.99 (Figure 3.6). The industry level of emissions was either 5.73 (low) or 9.23 (high). To arrive at these values, we considered the CO2 emissions of two paper brands in 2012 and 2010 as well as the industry average of CO2 emissions. We set our high industry value to be slightly above the highest value we observed among the two brands. We set our low industry value to be slightly lower than the lowest value we observed among the two brands. We set the low and high industry values as the respective first and third quartiles of our overall range and set the minimum and maximum *levels* and *changes* values for the brands in our charts accordingly. In order to make the numbers more salient to participants, we claimed that the numbers reflected the amount of CO2 emitted to produce one ream of paper. The participants in the *levels and changes* group were each also shown a value of the company's change in CO2 emissions compared to the average change in the industry. The value that each participant was shown for the company's change in emissions was randomized on a continuous scale between -7.00% and 7.00%, where a positive value indicated an increase in emissions over time. The industry value shown was either -4.00% or 4.00%, illustrating a reduction or increase in emissions over time, respectively. In this case, the fastest improvement (-7.00%) was approximately the *changes* value reported by one of the aforementioned paper brands between 2010 and 2012. In order to allow for a symmetrical chart, we set the maximum *changes* performance to be of equivalent magnitude in the opposite direction (+7.00%). Again, the low and high industry averages were approximately the first and third quartiles of the overall range. Participants were asked questions similar to those asked in Study 1a, but all questions were posed neutrally. For example, to detect warm-glow, participants were asked: "If I were to buy this product, I would feel (very bad to very good) about myself."

3.2.3 Results and Analysis.

Study 1b reinforced the impact of transparency. We segmented the treatment group into 36 possible groups based on the performance difference between the brand and the industry average across levels and changes. Within these groups, we compare the average purchase intention to the average purchase intention in the *control* group. Table 3.1 shows these differences, the corresponding significance levels, and the effect size as a percentage difference from the *control* average. The rows show how the brand's CO2 emissions *level* compares to the industry average. The columns shows how the brand's *change* in CO2 emissions compares to the industry average. In both cases, positive (negative) values mean that the brand is doing better (worse) than the industry average in the associated dimension. From the upper right section of the table, we see that transparent companies who are improving at a rate that is between 7.33 and 11 percentage points better than the industry average's rate and whose current levels of CO2 emissions are 3.49 to 5.24 units better (or lower) than that of the industry average receive a purchase intention that is 0.765 higher (20.179% higher) than the average purchase intention in the control group, which was 3.791 (M = 3.791, SD = 1.598, $p < 0.05$). Figure 3.7 maps these results, with green reflecting higher purchase intentions and red reflecting lower purchase intentions. The vertical axis shows how the brand's CO2 emissions *level* compares to the industry average.

Figure 3.6: Study 1b Images



Both charts were shown to all participants. The brand value varied along the scale indicated by the arrows while the industry average value took one of two values in each dimension. The order of the charts was randomized for each participant.

The horizontal axis shows how the brand's *change* in CO2 emissions compares to the industry average. In both axes, positive (negative) values mean that the brand is doing better (worse) than the industry average in the associated dimension. The dots indicate the areas in which the average purchase intention is significantly different from the average *control* value of 3.791. As in Study 1a, when the brand outperforms the industry average in *levels*, the likelihood of purchase is significantly higher than the control group, with larger dots reflecting a higher level of significance. From this figure, we see that when both *levels* and *changes* are presented, *levels* has the more dominant effect on likelihood of purchase. We note that although revealing levels of performance that rise above the industry average nearly always results in increased purchase intentions (in one case, up to 26.4%), revealing changes that are favorable relative to the industry average only increases purchase intentions when levels of performance are also better than the industry. Unlike in Study 1a, we observe certain instances in which transparency has a significantly negative impact, as large as -23.503%. When a brand is performing worse than the industry average in both *levels* and *changes* (as in the lower left corner of Figure 3.7), participants exhibited a significantly lower purchase intention. This insight is interesting as it suggests that there are situations in which transparency hurts the company relative to a condition of no transparency, confirming the risks of transparency [46].

Table 3.1: Summary Statistics: Difference in Average Purchase Intention from Control

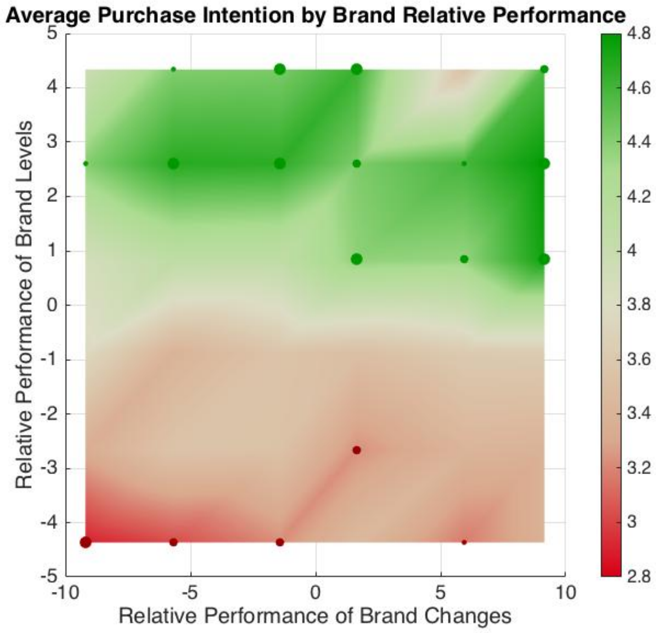
		Relative Changes						
		[-11, -7.33)	[-7.33, -3.67)	[-3.67, 0)	[0, 3.67)	[3.67, 7.33)	[7.33, 11)	Average
Relative Levels	[3.49, 5.24)	0.172 (4.537%)	0.626* (16.513%)	0.642*** (16.935%)	0.834*** (21.999%)	-0.261 (-6.885%)	0.765** (20.179%)	0.600*** (15.827%)
	[1.74, 3.49)	0.615* (16.223%)	0.889*** (23.450%)	0.876*** (23.107%)	0.635** (16.750%)	0.797* (21.023%)	1.002*** (26.431%)	0.789*** (20.812%)
	[0, 1.74)	0.100 (2.638%)	0.313 (8.256%)	0.296 (7.808%)	0.587*** (15.484%)	0.569** (15.009%)	0.956*** (25.218%)	0.494*** (13.031%)
	[-1.76, 0)	-0.031 (-0.818%)	-0.397 (-10.472%)	-0.235 (-6.199%)	-0.286 (-7.544%)	-0.177 (-4.669%)	-0.170 (-4.484%)	-0.221 (-5.830%)
	[-3.51, -1.76)	-0.446 (-11.765%)	-0.232 (-6.120%)	-0.251 (-6.621%)	-0.561** (-14.798%)	-0.382 (-10.076%)	-0.400 (-10.551%)	-0.381 (-10.050%)
	[-5.26, -3.51)	-0.891*** (-23.503%)	-0.759** (-20.021%)	-0.569** (-15.009%)	-0.340 (-8.969%)	-0.618* (-16.302%)	-0.404 (-10.657%)	-0.570*** (-15.036%)
	Average	-0.049 (-1.293%)	-0.001 (-0.026%)	0.088 (2.321%)	0.179 (4.722%)	0.019 (0.501%)	0.384* (10.129%)	0.115 (3.034%)

The rows show the performance difference between brand and the industry average in the *levels* dimension, with positive values indicating that the brand is performing better than the industry. The columns show the performance difference between brand and the industry average in the *changes* dimension, with positive values indicating that the brand is performing better than the industry. We observe the strongest purchase intentions when the brand is performing better than the industry average in *levels*. From this study, we observe scenarios in which transparency negatively impact purchase intention. Effect sizes are included as percentages in parentheses below the absolute differences. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3.3 Customer Transparency and Energy Consumption

Although Studies 1a and 1b illustrate the impact of relative transparency of a company's processes, Study 2 considers the impact of relative performance transparency as it pertains to customers. We operationalize customer transparency in the energy consumption domain, building on a large volume of literature that explores the importance of relative performance feedback in impacting an individual's sustainable behavior. In Study 2, we used all four cells of the 2 x 2 design: *control*, *levels only*, *changes only*, and *levels and changes*. We analyze the data, given the specific treatments, in the same way as we did in Studies 1a and 1b.

Figure 3.7: Heat Map: Average Purchase Intention by Brand Performance



This heat map reveals the impact of transparency when both relative *levels* and relative *changes* are disclosed. We note that the gradient from green to red is stronger in the vertical dimension, indicating the dominance of *levels* in impacting purchase intention.

3.3.1 Participants.

In this study, we had 3,780 participants (44.2% male, M_{age} = 35.01, SD = 11.44) complete this study for 50 cents. Participants were shown a household's hypothetical energy bill and asked to answer questions relating to this household's hypothetical energy consumption in the future. The three treatment groups were also shown charts that illustrated either the current consumption levels of the household (*levels only*), the change in consumption levels of the household (*changes only*), or both (*levels and changes*) compared to the neighborhood average. We only retained data from participants who correctly answered two attention check questions, one of which asked participants to select a predetermined response and the other which asked for the subject of the survey (energy consumption) (N=3412, 44.2% male, M_{age} = 35.1, SD = 11.42).

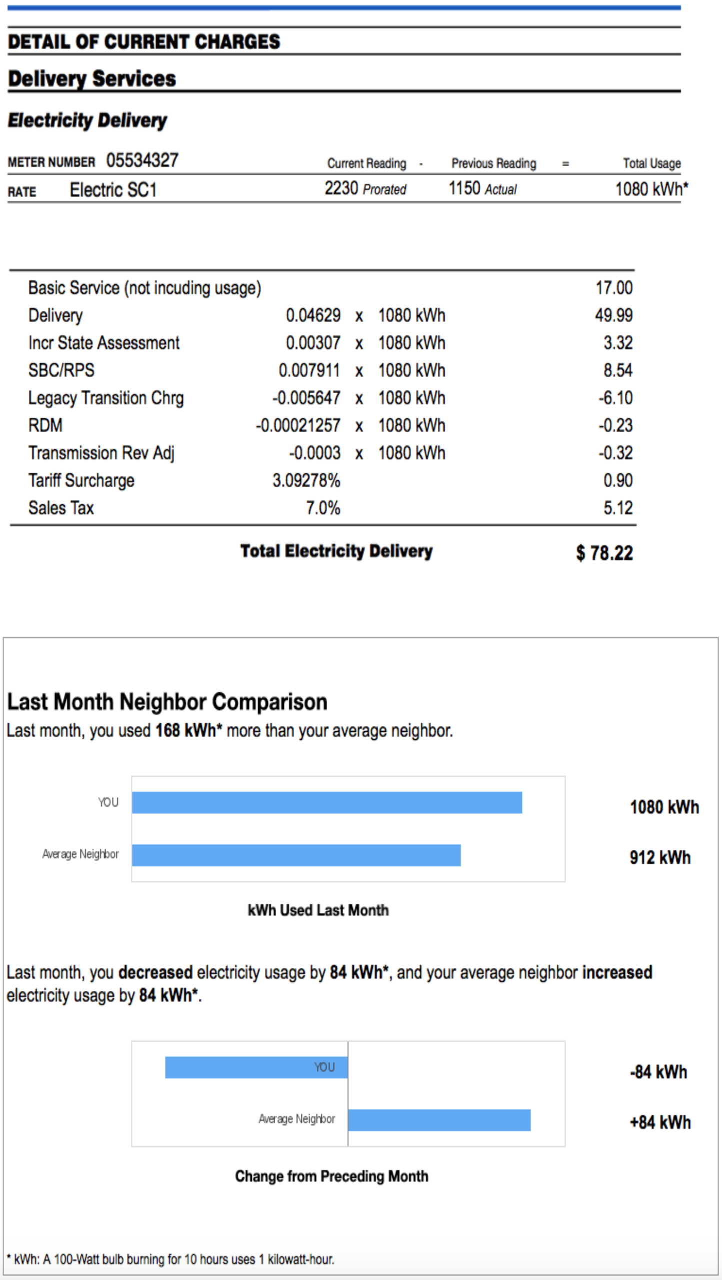
3.3.2 Design and Procedure.

In this study, the participants were randomly assigned to one of four groups: the *control* group, the *levels only* group, the *changes only* group, and the *levels and changes* group. All groups were shown an energy bill with the household's current consumption level. Within the *control* group, participants were randomly assigned to one of six equidistant values on a discretized scale between 660 and 1,164. However, only the three treatment groups were shown a comparison to the neighborhood average. The *levels only* group saw a chart that revealed the average neighborhood level of energy consumption to be 912 kilowatt-hours (kWh), which is approximately the average monthly electricity consumption of a U.S. residential utility customer, according to the U.S. Energy Information Administration [57]. The maximum value of a household's energy consumption level (1,164) was 90% of the monthly average of the state with the maximum annual electricity consumption. We allowed a buffer to ensure a realistic possibility of increasing from an initial level of 1,164. We then selected 660 as the minimum to ensure equal likelihood of being above or below the neighborhood average. The *changes only* group saw a chart that revealed the neighborhood's average change in energy consumption from the prior month to be +84 kWh (an increase in consumption from the prior month) or -84 kWh (a decrease in consumption from the prior month). The household change in energy consumption from the prior month took one of six equidistant values on a discretized scale between -126 and +126 kWh. These maximum and minimum values were chosen to ensure that no household would ever be outside the minimum or maximum monthly consumption when considering the average consumption of all U.S. states. In total, there were 108 possible conditions of relative performance. We showed the *levels and changes* group both charts, randomizing which chart was shown above the other (Figure 3.8).

3.3.3 Dependent Measures.

We again used 7-point Likert scale questions to determine the likelihood of reducing energy consumption in the future, asking participants: "How likely would most people be to reduce energy consumption in the next month if they were to receive this bill (assuming similar climate)?" It is important to note that the questions were phrased in the third person, as participants had to answer questions about another household's likelihood to reduce consumption. Our methodology is consistent with previous research that attempts to extract participants' true feelings when such feelings may be widely considered unfavorable. For example, previous research has shown that people may not readily admit their own true responses, if they may be perceived as socially undesirable; as such, asking them to speculate about others' socially undesirable responses may capture a more accurate measure of their own [15]. We conducted a pilot study with 240 participants, in which we confirmed that asking the questions in the

Figure 3.8: Study 2 Images



DETAIL OF CURRENT CHARGES

Delivery Services

Electricity Delivery

METER NUMBER 05534327 — Current Reading - Previous Reading = Total Usage

RATE Electric SC1 — 2230 *Prorated* — 1150 *Actual* — 1080 kWh*

Basic Service (not incuding usage)				17.00
Delivery	0.04629	x	1080 kWh	49.99
Incr State Assessment	0.00307	x	1080 kWh	3.32
SBC/RPS	0.007911	x	1080 kWh	8.54
Legacy Transition Chrg	-0.005647	x	1080 kWh	-6.10
RDM	-0.00021257	x	1080 kWh	-0.23
Transmission Rev Adj	-0.0003	x	1080 kWh	-0.32
Tariff Surcharge	3.09278%			0.90
Sales Tax	7.0%			5.12
		Total Electricity Delivery		**$ 78.22**

This is the image shown to the *levels and changes* group, with the order of the *levels* and *changes* charts randomized. The *control* group saw only the top half of this bill, excluding the two charts at the bottom.

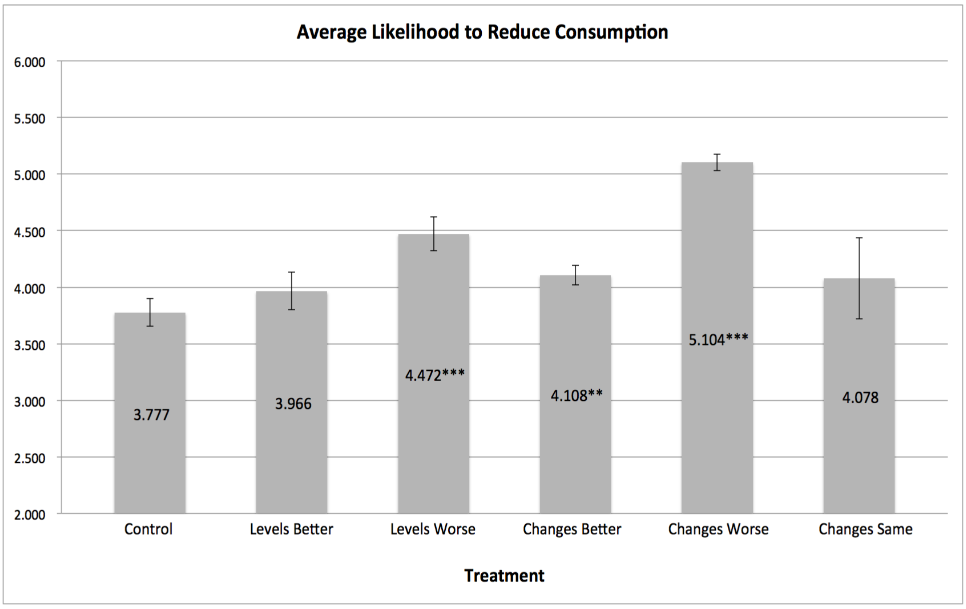
third person rather than the first person elicited responses that were less artificially inflated in the socially accepted direction.[1] To explore possible mechanisms for the conservation behavior we expected to observe, we also asked participants questions relating to intrinsic motivations, extrinsic motivations, and reputation or image motivations [16]. To investigate the impact of the warm-glow motive, we use an adapted two-item scale in which we asked participants the extent to which they agreed with the following statements: "Most people if they received this bill would feel bad about not reducing their energy consumption if they had the chance" and "Most people if they received this bill would feel good if they were to reduce their energy consumption" [55]. We found low correlation (0.257) between these two items and as such treated them separately in our analysis. We also asked a question to elicit the monetary extrinsic motivation to reduce consumption, asking participants: "Saving money would be an important factor in most people's decision to reduce consumption if they received this bill." To explore reputation or image motivations, we asked three questions to elicit the importance of prestige: "By reducing their energy consumption, most people if they received this bill would think they make a good impression," "By reducing their energy consumption, most people if they received this bill would think they satisfy the expectations of others," and "By reducing their energy consumption, most people if they received this bill would think they are valued by others" [29]. Finally to ensure the validity of the data, we asked questions regarding the credibility of the bill and the trustworthiness of the energy company. We found no impact of either measure on likelihood of reduction of consumption.

3.3.4 Results and Analysis.

We conduct our initial analyses to parallel the analysis conducted in Study 1a. We compare the likelihood of reduction among the following three groups: *control*, *levels only*, and *changes only*; within *levels only* and *changes only*, we further compare conditions in which a household performs better or worse than the neighborhood average. We pooled the results from all energy bills in the *control* group, regardless of value of the bill, to find an average likelihood of reduction of 3.777 using a Likert-type scale ($M = 3.777$, $SD = 1.666$). A Wilcoxon rank sum test again illustrates the significant impact of the treatment conditions compared to the *control*, as nearly all treatment conditions resulted in a significantly increased likelihood of reduction in the subsequent period. The transparency condition that showed the largest difference in likelihood

[1] From our pilot study, the likelihood to reduce consumption in the future was lower in the third person scenario ($M = 4.043$, $SD = 1.551$) than in the first person scenario ($M = 4.389$, $SD = 1.682$, $W = 7393.5$, $p = 0.088$).

Figure 3.9: Average Likelihood to Reduce Consumption



When the household fared worse than the neighborhood average in *levels* or in *changes*, we observed a significantly higher likelihood to reduce consumption than the control ($p = 0.002$ and $p < 0.001$, respectively). When the household fared better than the neighborhood average in *changes*, we still observed a significantly higher likelihood to reduce consumption than the control ($p = 0.039$). In no condition did transparency negatively affect the likelihood to reduce, although it was least helpful when it revealed that the household fared better than the neighborhood in *levels*, in which case no significant difference was found compared to the *control*. Standard error bars are included. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

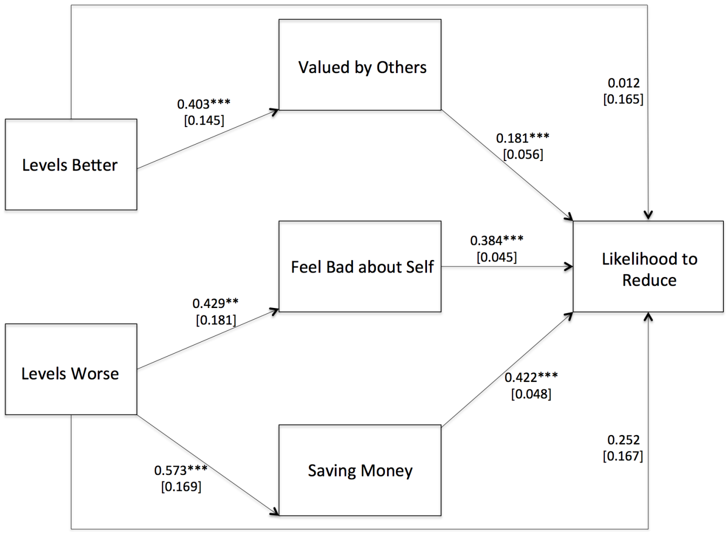
of reduction compared to the *control* was when the household was faring worse than the neighborhood average in *change* in consumption ($M = 5.104$, $SD = 1.272$, $W = 15732$, $p < 0.001$) (Figure 3.9). The *levels worse* group, in which the household had consumed more energy in the month than the neighborhood average, also showed a significantly higher likelihood of reduction ($M = 4.472$, $SD = 1.415$, $W = 6287$, $p = 0.002$). Intuitively, we understand that revealing worse performance would tend to encourage people to want to perform better. Interestingly, in the *changes* dimension, revealing better performance also resulted in a significantly higher likelihood to reduce at ($M = 4.108$, $SD = 1.552$, $W = 25916$, $p = 0.039$), suggesting the importance of transparency in this dimension regardless of relative performance. We note that revealing *change* with a value identical to the household's neighborhood average ($M = 4.078$, $SD = 1.540$) did not result in a significantly different likelihood to reduce consumption than the *control* group although it was still directionally higher. There was no significance between the *levels better* group and the *control* group. In this domain, although we do not see a scenario in which transparency is demotivating, we find that transparency is least helpful when it reveals that the consumer is performing better than average in the *levels* dimension.

We also note that *changes* has a stronger impact in motivation reduction than *levels*. When comparing those participants who were shown the household's *changes only* to the *control* group, a regression reveals that the coefficient of transparency ($\beta = 0.734$, $p < 0.001$) is higher and more significant than the regression coefficient of transparency when we compare those participants who were shown the household's *levels only* to the *control* group ($\beta = 0.442$, $p = 0.009$). Furthermore, we find that people are driven most by transparency that reveals the household is faring worse than their neighbors in the *changes* dimension, as the coefficient on the performance difference in *changes* between a household and its neighbors is negative and significant ($\beta = -0.003$, $p < 0.001$). This is in contrast to the purchase domain, in which customers are most motivated by brands faring better than the industry average.

We again used structural equation models to conduct a path analysis to explore the mechanisms for the observed behavior. In this domain, we find that transparency affects three mechanisms: feeling valued by others, feeling bad about not reducing consumption when the household had the chance to do so, and the importance of saving money (Figure 3.10). Within *levels*, revealing worse performance is positively associated with feeling badly about oneself ($\beta = 0.429$, $p = 0.018$) and with an increased importance on saving money ($\beta = 0.573$, $p = 0.001$). Both feeling bad about oneself and the importance of saving money are positively associated with the likelihood to reduce ($\beta = 0.384$, $p < 0.001$ and $\beta = 0.422$, $p < 0.001$, respectively). We note that between the two, the importance of saving money is the stronger mechanism driving behavior. We also find that revealing better performance within *levels* is positively associated with feeling valued by others ($\beta = 0.403$, $p = 0.005$), another significant driver in the likelihood to reduce ($\beta = 0.181$, $p = 0.001$). This offers a possible reason as to why revealing positive performance still does not hurt likelihood to reduce consumption, as one might have expected from the boomerang effect [50]. The importance of feeling valued serves to counteract the desire to increase consumption. This model exhibits a strong fit (CFI (0.880) and RMSEA (0.108) ($p < 0.01$)) (Figure 3.10).

Within *changes*, we observe similar trends. Revealing worse performance is also positively associated with feeling badly about oneself ($\beta = 0.793$, $p < 0.001$) and with an increased importance on saving money ($\beta = 0.510$, $p < 0.001$), both of which are significant drivers of likelihood of reduction ($\beta = 0.328$, $p < 0.001$ and $\beta = 0.395$, $p < 0.001$, respectively). However, in contrast to the *levels* dimension, revealing worse performance in the *changes* dimension seems to have a stronger effect on feeling badly about oneself than on the importance of saving

Figure 3.10: Study 2a Path Analysis: Levels

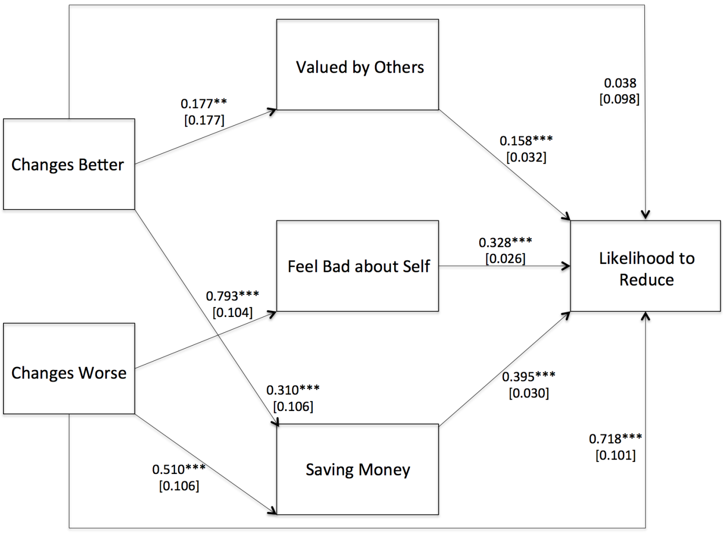


Beta coefficients are displayed for the *levels* transparency in Study 2a. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are presented in brackets. While revealing worse performance is positively associated with customers feeling bad about themselves and the importance of saving money, revealing better performance is positively associated with feeling valued by others. All three mechanisms are significant drivers of likelihood to reduce consumption.

money. This is likely because the overall amount owed from the bill is calculated based on the absolute level on consumption, and showing the *levels* charts emphasizes this amount. Finally, as in *levels*, revealing better performance within *changes* is positively associated with feeling valued by others ($\beta = 0.177$, $p = 0.040$), another significant driver in the likelihood to reduce ($\beta = 0.158$, $p < 0.001$). This model exhibits a strong fit (CFI (0.867) and RMSEA (0.135) ($p < 0.01$)) (Figure 3.11).

To determine which dimension had a stronger impact on behavior in this domain, we analyzed the results from the *levels and changes* group. We segmented this treatment group into 54 possible groups based on the difference in magnitude between the household and the neighborhood average across levels and changes. Within each of these groups, we compared the average likelihood to reduce to the average likelihood to reduce in the control group, which was 3.777. Table 3.2 reveals these differences along with the corresponding significance levels and effect sizes. The rows show how the household's *level* of consumption differ from the neighborhood average, and the columns show how the household's *change* in consumption from the prior month compares to the neighborhood average. In both cases, positive (negative) values mean that the household is faring better (worse) than the neighborhood average. From Table 3.2, we see that the bottom left quadrant showed the highest likelihood to reduce values, up to 38.787%. That is, when a household was performing worse than the neighborhood in both dimensions,

Figure 3.11: Study 2a Path Analysis: Changes



Beta coefficients are displayed for the *changes* transparency in Study 2a. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are presented in brackets. We note that revealing worse performance in *changes* is positively associated with customers feeling bad about themselves to a greater degree than was observed in revealing worse performance in *levels*. Conversely, revealing worse performance in *changes* is positively associated with the importance of saving money to a lesser degree than was observed in revealing worse performance in *levels*. As with *levels*, revealing worse performance in *changes* is positively associated with feeling valued by others. All three mechanisms are significant drivers of likelihood to reduce consumption.

the household was more likely to show a high likelihood of reduction in the following period. Conversely, the top right section of the table shows the lowest likelihood to reduce values. This suggests that when a household was performing better than their neighbors in both dimensions– consuming a low amount of energy and also drastically reducing energy consumption– their likelihood to reduce was not significantly different from the *control* group. Under no circumstances did transparency result in a significantly lower likelihood to reduce than the *control*. We map our results in Figure 3.12, with green reflecting higher likelihood of reduction values and red reflecting lower likelihood of reduction values. Again, the dots indicate the areas in which the likelihood of reduction significantly differs from the control value of 3.777. From this figure, we see that revealing *changes* has a more dominant effect on the likelihood of reduction. The left half of the figure, which illustrates the scenarios in which the household fares worse than the neighborhood in *changes*, is predominantly green. This suggests that when a household is told that they are reducing consumption at a slower rate than the neighborhood average, the household is compelled to reduce consumption in the subsequent period, regardless of their current *level* of consumption. Conversely, the bottom half of the figure illustrates when the household is faring worse than the neighborhood average in terms of *level* of consumption. While also predominantly green, this section shows more of a gradient between the left and the right. The

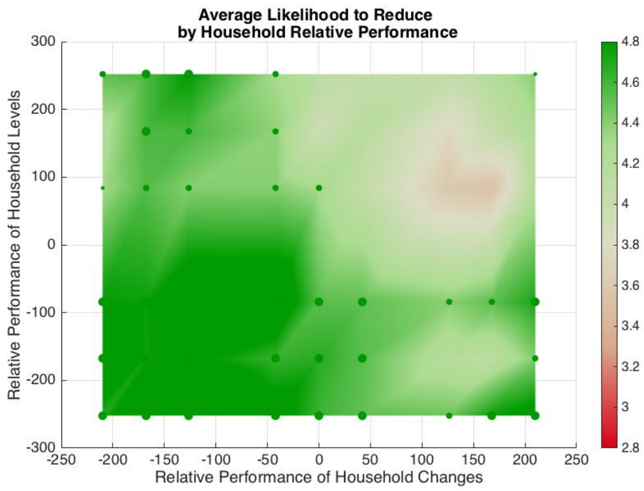
Table 3.2: Summary Statistics: Difference in Average Likelihood to Reduce Consumption from Control

		Relative Changes									
		-210	-168	-126	-42	0	42	126	168	210	Average
Relative Levels	252	0.738** (19.539%)	0.794*** (21.022%)	1.017*** (26.926%)	0.529** (14.006%)	0.348 (9.214%)	0.314 (8.313%)	0.366 (9.690%)	0.429 (11.358%)	0.630* (16.680%)	0.534*** (14.138%)
	168	0.458 (12.126%)	0.794*** (21.022%)	0.789** (20.890%)	0.598** (15.833%)	0.177 (4.686%)	0.382 (10.114%)	-0.027 (-0.715%)	0.255 (6.751%)	0.496 (13.132%)	0.424*** (11.226%)
	84	0.537* (14.218%)	0.766** (20.281%)	0.629* (16.653%)	0.623** (16.495%)	0.517** (13.688%)	0.314 (8.313%)	-0.255 (-6.751%)	-0.234 (-6.195%)	0.416 (11.014%)	0.413*** (10.935%)
	-84	1.011*** (26.767%)	0.989*** (26.185%)	1.255*** (33.227%)	1.271*** (33.651%)	0.749*** (19.831%)	0.738*** (19.539%)	0.617** (16.336%)	0.689** (18.242%)	0.965*** (25.549%)	0.921*** (24.384%)
	-168	1.348*** (35.690%)	0.980*** (25.947%)	1.080*** (28.594%)	0.859*** (22.743%)	0.901*** (23.855%)	0.754*** (19.963%)	0.399 (10.564%)	0.344 (9.108%)	0.635** (16.812%)	0.814*** (21.551%)
	-252	0.912*** (24.146%)	1.340*** (35.478%)	1.465*** (38.787%)	1.135*** (30.050%)	0.844*** (22.346%)	0.782*** (20.704%)	0.692** (18.321%)	0.980*** (25.947%)	1.129*** (29.891%)	1.011*** (26.767%)
	Average	0.825*** (21.843%)	0.941*** (24.914%)	1.044*** (27.641%)	0.837*** (22.160%)	0.581*** (15.383%)	0.542*** (14.350%)	0.327*** (8.658%)	0.402*** (10.643%)	0.712*** (18.851%)	0.684*** (18.110%)

The rows show the performance difference between the household and the neighborhood average in the *levels* dimension, with positive values indicating that the household is performing better than the neighborhood. The columns show the performance difference between household and the neighborhood average in the *changes* dimension, with positive values indicating that the brand is performing better than the industry. We observe the strongest likelihoods of reduction in consumption when the household is performing worse than the industry average in *changes*. From this study, we observe that transparency positively impacts likelihood of reduction in energy consumption in most scenarios. Effect sizes are included as percentages in parentheses below the absolute differences. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

bottom left quadrant is the most green, revealing that likelihood to reduce is strongest when the household fares worse than the neighborhood in both dimensions. The bottom right quadrant is less green, suggesting that the likelihood to reduce consumption that is induced by doing poorly in *levels* is mitigated by doing better in *changes*.

Figure 3.12: Heat Map: Average Likelihood to Reduce Consumption by Household Relative Performance



This heat map reveals the impact of transparency when both relative *levels* and relative *changes* are disclosed. We note that the gradient from green to red is stronger in the horizontal dimension, indicating the dominance of *changes* in impacting likelihood to reduce consumption.

Chapter 4

Discussion

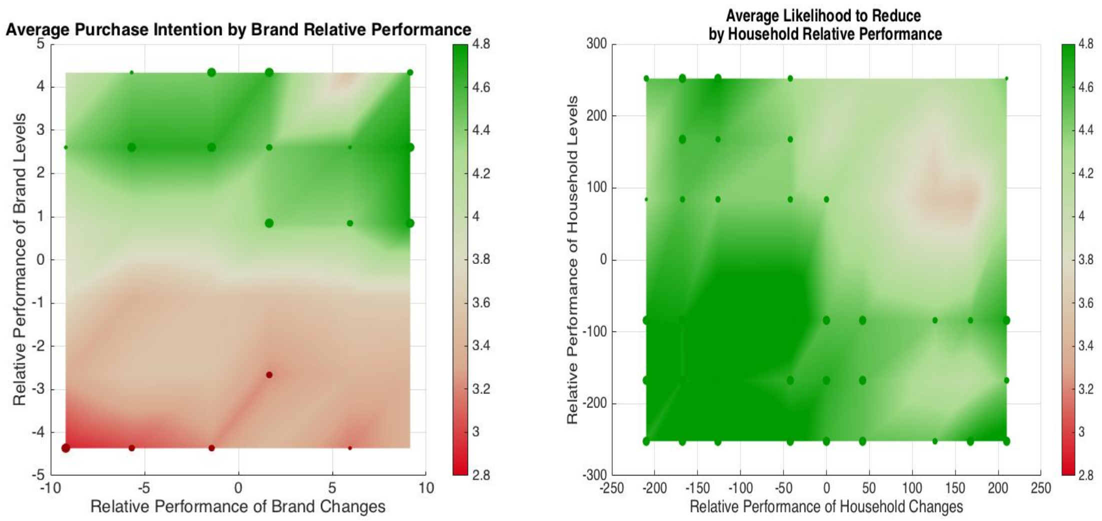
To our knowledge, we are the first in the literature to demonstrate how different dimensions of relative performance transparency (current performance *level* versus *change* in performance) that focus on different types of transparency (companies' processes versus customers) distinctively impact consumer behavior, as operationalized in the product purchase and energy consumption domains. Our results can be extended to a variety of domains, from schools that report standardized test scores to charities that disclose how they spend donations to companies encouraging their employees to save money. Our focus has been on sustainability. By conducting variations of 2 x 2 design studies, we determined the impact of revealing *levels only*, *changes only*, and both *levels and changes* compared to a control group that saw no transparency.

Within the process transparency realm, we find that a company that discloses its relative performance in one domain only (*levels* or *changes*) is not hurt by this disclosure. That is, when the company performs better than the industry average, we observe an increase in purchase intention; when the company performs worse than the industry average, we see either an increase in purchase intention or no change. This suggests that consumers value transparency regardless of the information being revealed, reinforcing the importance of being a leader in disclosure as studied by [28]. Furthermore, our structural estimation models reveal that consumers' positive feelings towards themselves are a strong indicator of purchase intention. When the company is performing well on either dimension (*levels* or *changes*), consumers feel better about themselves for purchasing the product, indicating the presence of a warm-glow motive. This reinforces the notion that consumers show increased purchase intention for items associated with worthy causes, as set forth by other cause-marketing research and labeling literature previously discussed. When companies reveal their performance along both *levels* and *changes*, we find *levels* to be a more motivating force in influencing behavior. In nearly all instances when the company is performing better than the industry average in *levels*, consumers exhibit a significantly higher purchase intention, regardless of the performance in the *changes* dimension. The only exception is when the company fares only marginally better in *levels* and simultaneously fares worse in *changes*, in which case purchase intention is not significantly different from the control group who sees no transparency. This suggests that in process transparency, consumers who make purchasing decisions are primarily concerned with the ultimate output of a firm, as opposed to its trajectory over time.

Interestingly, when both dimensions of information are revealed, we find instances in which transparency is harmful to the company: when the company is performing much worse in the *levels* dimension. Thus, when companies are performing much worse than the industry on average in *levels*, it may be more beneficial for companies to not disclose *changes*. Disclosing unfavorable *levels* alone does not reduce purchase intention, even though it does negatively impact consumers' feelings towards themselves, their trust towards the company, and their perception of product quality. The lack of significant difference from the *control* can perhaps be accounted for by customers valuing and rewarding the act of transparency despite these negative feelings. However, the addition of disclosing information regarding relative performance in the *changes* dimension can result in reduced purchase intention, even if the performance in the *changes* dimension is more favorable than the industry average. Further research can be done on the mechanisms operating when both types of transparency are revealed and particularly why revealing both dimensions may be harmful. Perhaps the value of transparency is mitigated as more information is revealed because consumers attribute less effort to the disclosures.

Within the realm of customer transparency, we see no evidence of unfavorable behavior induced by any dimension or amount of transparency. While mechanisms for reduced consumption through transparency include feelings towards oneself, as was the case in the product purchase domain, we find that feeling bad about oneself is a stronger motivator than feeling good about oneself. This is perhaps because the energy consumption domain depicts behavior that has happened in the past as opposed to prospective behavior as is depicted in the product purchase case. Furthermore, feeling valued by others is an important mechanism that was not identified in the purchase domain, perhaps because energy consumption has a more direct link to someone's impact on the environment than purchasing an environmentally-conscious product. We also see the impact of an extrinsic motive as people recognize the importance of saving money. In contrast to the purchase domain, we find that when both dimensions of information are revealed, *changes* is the more motivating factor in influencing behavior. A side-by-side comparison illustrates the stark contrast between the power of *changes* in process transparency and customer transparency (Figure 4.1). While there is a clearly visible horizontal line between the green and red sections in the purchase intention heat map, emphasizing the importance of *levels*, there is no such line in the energy consumption heat map. In the latter case, the green seems to be more dense around the left half of the map and lighter towards the right, suggesting that if any dividing line existed, it would be a vertical one, emphasizing the importance of *changes*.

Figure 4.1: Comparison of Heat Maps



These images are identical to those presented in Figures 3.7 and 3.12. They have been reproduced for ease of comparison. We note that within the product purchase domain, the gradient from green to red is stronger in the vertical dimension, indicating the dominance of *levels* in motivating sustainable purchase behavior. Conversely, within the energy consumption domain, the gradient from green to red is stronger in the horizontal dimension, indicating the dominance of *changes* in motivating sustainable consumption behavior.

In the customer transparency domain, while further research must be done on the mechanisms when both dimensions of transparency are revealed simultaneously, one possible reason for the importance of *changes* is that people feel that they have more power to affect their *changes* value; they may feel as though external factors out of their control contribute to differences in consumption levels, such as the number of people in a household or the type of energy required. Alternatively, perhaps the cost of making changes in the consumption space is greater than the cost of making changes in the paper production space and therefore is more valued. Finally, given that the action of energy consumption is inherently one that occurs over a period of time– whereas product purchase is often a one-time action– participants may be more inclined to give *changes* more weight in the energy consumption domain.

Further directions for this research include exploring framing effects through reference points or language. For example, while we recognize from previous literature that peer reference groups are most effective when the peer group is most similar to the target [22], in the customer transparency realm, we could experiment with the optimal type of reference point that households are shown: perhaps the most efficient neighbors as opposed to the average neighbor or a particular quantile of performance. Additionally, we could experiment with showing households their neighborhood's performance compared to other neighborhoods in the county, shaping the behavior as a community goal as opposed to an individual goal. Nevertheless, we would need to be wary of evidence of oppositional reactions or boomerang effects, in which households may shift towards the less desirable behavior. Furthermore, the longevity of the behavior based on our results has yet to be explored, and the sustainability of behavioral changes at the individual level with respect to a company or to oneself has yet to be determined. To conclude, our research presents valuable insights into the impact of relative performance transparency on sustainable behavior. We hope to illustrate that in addition to government-sanctioned policies and initiatives at a macro level, behavioral science can be an instrumental tool in enhancing sustainability in operations and in highlighting the importance of environmental responsibility.

Appendix A

Measures

A.1 Study 1A and 1B Measures

1. How likely are you to purchase this product? (Very Unlikely - Very Likely)
2. What is your perceived quality of this product? (Very Poor - Very Good)
3. How fair do you think the price of $14.55 is for this product? (Very Unfair - Very Fair)[1]
4. Up to what price (in USD) would you pay for this product?[2]
5. How likely are you to recommend this product to a friend or colleague? (Very Unlikely - Very Likely)[3]
6. How likely are you to consider other brands of paper? (Very Unlikely - Very Likely)[4]
7. My feelings towards this company can best be described as: (Very Dissatisfied - Very Satisfied)
8. Compared to competitors, this company has a(n) ___ reputation. (One of the Worst - Average - One of the Best)
9. My overall trust in the company is: (Very Low - Very High)
10. To what extent do you agree with the following statements (Strongly Disagree - Strongly Agree)

[1] Only asked in Study 1a.
[2] Participants could choose a value along a scale between $5 and $25.
[3] Only asked in Study 1a.
[4] Only asked in Study 1a.

- This company appears more trustworthy than others from which I've purchased.[5]
- This company feels morally obligated to be environmentally responsible.

11. How familiar are you with this company? (Very Unfamiliar - Very Familiar)[6]

12. To what extent do you agree with the following statements (Strongly Disagree - Strongly Agree)

    - I would feel good if I bought this product.[7]
    - I would discuss this purchase with others if I bought this product.[8]
    - I would enhance my reputation if I bought this product. [9]
    - The issue of carbon dioxide emissions is important to me.[10]
    - Carbon dioxide emissions directly impact my life.[11]
    - The issue of carbon dioxide emissions directly impacts my purchase decisions.[12]
    - Please select "Somewhat Agree" for this row only.[13]
    - What product did you see in this survey (T-shirts, Laundry Detergent, Paper)[14][15]

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[5] Only asked in Study 1a.
[6] Only asked in Study 1a.
[7] Rephrased in Study 1b: If I were to buy this product, I would feel ___ about myself. (Very Bad - Very Good)
[8] Only asked in Study 1a.
[9] Rephrased in Study 1b: If I were to buy this product, my reputation would ___. (Significantly Worsen - Significantly Improve)
[10] Only asked in Study 1a.
[11] Only asked in Study 1a.
[12] Only asked in Study 1a.
[13] Attention check.
[14] Attention check.
[15] Only asked in Study 1b.

A.2 Study 2 Measures

1. How likely would most people be to reduce energy consumption in the next month if they received this bill (assuming similar climate)? (Very Unlikely - Very Likely)

2. Most people if they received this bill would feel bad about not reducing their energy consumption if they had the chance. (Strongly Disagree - Strongly Agree)

3. Most people if they received this bill would feel good if they were to reduce their energy consumption. (Strongly Disagree - Strongly Agree)

4. Saving money would be an important factor in most people's decision to reduce energy consumption if they received this bill. (Strongly Disagree - Strongly Agree)

5. By reducing their energy consumption, most people if they received this bill would think they make a good impression. (Strongly Disagree - Strongly Agree)

6. By reducing their energy consumption, most people if they received this bill would think they satisfy the expectations of others. (Strongly Disagree - Strongly Agree)

7. By reducing their energy consumption, most people if they received this bill would think they are valued by others. (Strongly Disagree - Strongly Agree)

8. Please select "Somewhat Agree" for this row only.[16]

9. The overall trust by most people if they received this bill towards this company would be: (Very Low - Very High)

10. Most people if they received this bill would find this company ___ trustworthy than other utilities companies. (Significantly Less - Significantly More)

11. Most people if they received this bill would believe that the credibility of the information on this bill is: (Very Low - Very High)

[16] Attention check.

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Appendix B

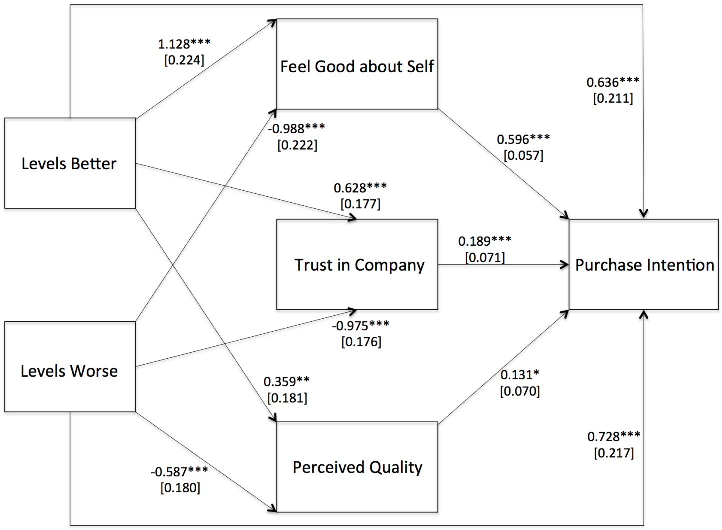
Structural Equation Modeling

B.1 Path Analysis

To identify the underlying mechanisms driving the observed behavior in each study, we use structural equation modeling to conduct a path analysis. Structural equation modeling (SEM) is a statistical tool used to analyze multivariate data. Is is a confirmatory technique which requires a proposed model to be tested. As opposed to ordinary linear regression, SEM allows for the specification of linear relationships among multiple independent and dependent variables, which can be either measured variables (observed) or latent constructs (unobserved constructs that are identified by multiple observed measures). In our results and analysis, we use a special case of SEM called *path analysis*, which is used for cases in which all variables are measured. Given that our analysis relied on single-item scales, the use of path analysis is appropriate. In this method, the sample covariance matrix of the variables (S) serves as the data. The goal is to propose a model that produces a population covariance matrix (Σ) consistent with the sample covariance matrix. Thus, we propose a model and use path analysis to estimate basic parameters from the data. We then compute an estimate of the population covariance matrix ($\hat{\Sigma}$). Path analysis allows us to evaluate the fit of the model by comparing S and $\hat{\Sigma}$; when the model exhibits a strong fit, we expect S and $\hat{\Sigma}$ to be similar as they both estimate Σ [49, 36].

Whereas S will always have $p(p+1)/2$ unique elements (where p is the number of variables), Σ will have fewer unique distinct elements if our proposed model is valid. As an example, we will focus on the *levels* path analysis diagram from Study 1a, which has been reproduced in the appendix. As is convention, one-way directional arrows represent regression coefficients. Residuals are not shown.

Figure B.1: Study 1a Path Analysis: Levels



Reproduced from Study 1a.

The system of regression equations from our path analysis is as follows:

$$
\begin{aligned}
FeelGood =& \beta_1 LevelsBetter + \beta_2 LevelsWorse + \xi_{FG} \\
TrustCompany =& \beta_3 LevelsBetter + \beta_4 LevelsWorse + \xi_{TC} \\
PerceivedQuality =& \beta_5 LevelsBetter + \beta_6 LevelsWorse + \xi_{PQ} \\
PurchaseIntention =& \beta_7 LevelsBetter + \beta_8 LevelsWorse \\
& + \beta_9 FeelGood + \beta_{10} TrustCompany + \beta_{11} PerceivedQuality + \xi_{PI}
\end{aligned}
$$

If our model were to hold, the covariance between *LevelsBetter* and *FeelGood* can be rewritten as $cov(LevelsBetter, \beta_1 LevelsBetter + \beta_2 LevelsWorse)$, which would only require the regression coefficients, variance of $LevelsBetter$, and covariance between $LevelsBetter$ and $LevelsWorse$. By similarly accounting for the covariance for all elements in Σ, we arrive at the necessary *model parameters*, denoted by vector Θ. Using a *fitting function* that minimizes some function of the residuals between S and $\hat{\Sigma}$ (denoted by $F(S, \hat{\Sigma})$), we can estimate Θ. The package we use employs a maximum likelihood fitting function, as is most common. This method assumes multivariate normality of the joint distribution of data, yet the parameters it yields are usually robust to the violation of this assumption [49]. We then compute a test statistic $T = (N-1)F(S, \hat{\Sigma})$ that approximately follows a chi-square distribution. Our degrees of freedom *df* are equal to the number of unique elements from our covariance matrix (equal to $p(p+1)/2$), less the number of model parameters in Θ. We test the null hypothesis that

$\Sigma = \Sigma(\Theta)$, hoping that we will not reject the null.

The reason for imposing a model upfront is clear. Without doing so, we would have a *saturated model* in which every possible relationship among all variables would be analyzed, resulting in zero degrees of freedom. This would not provide an evaluation of the overall model fit but rather be identical to multiple ordinary linear regressions. Conversely, assuming that all variables were independent from one another would result in the *independence model*, in which all covariances among different variables are assumed to be zero; the only nonzero elements in the covariance matrix are the variances of each variable along the diagonal.

However, in practice, the aforementioned statistical test has significant limitations, including its sensitivity to sample size. As such, it is usually considered in conjunction with various fit indices when determining the validity of the model [26]. In our results, we consider two of the most commonly used and highly recommended fit indices, comparative fit index (CFI) and root-mean squared error of approximation (RMSEA). The CFI compares the sample covariance matrix from the proposed model with that of the *independence model* (the null model). It is given by

$$1 - \frac{(\chi_M^2 - df_M)}{(\chi_N^2 - df_N)} \tag{B.1}$$

where χ_M^2 is the proposed model chi-square and χ_N^2 is the null chi-square. CFI values range from 0.0 to 1.0. When the model is correct, the CFI value is close to 1.0 The RMSEA is given by

$$\sqrt{\frac{\hat{\lambda}_M^2}{(N-1)df_N}} \tag{B.2}$$

where $\hat{\lambda}_M^2$ is a measure of noncentrality for the proposed model. The RMSEA measures the average amount of misfit in the model per degree of freedom. Low values indicate better fit. In accordance with existing literature, we use these two fit indices to evaluate the strength of all structural equation models in our analysis.

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