# A behavioral option value model 

of consumer product set choice

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# A BEHAVIORAL OPTION VALUE MODEL OF CONSUMER PRODUCT SET 

## CHOICE

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#### Abstract

Consumers often purchase products for future use when the utility of these products in the future is still uncertain. One way to accommodate this uncertainty, is for firms to offer choice flexibility by allowing consumers to initially choose a set of products from which they can choose a single product in the future. Such flexibility creates option value for consumers because they can benefit from the utility information that is revealed in the future. This paper develops a formal utility model for consumers' behavioral valuation of this option value of product sets. It proposes a new three-stage method that combines choice experiment-based decision elicitation and econometric modeling to estimate consumers' behavioral option value. The results of four experiments provide empirical support for the proposed components of the consumer product set option value model. They show that consumers do indeed take into account option value when selecting product sets from which to choose an alternative in the future. They also show that, behaviorally, consumers overweigh option value and apply decision weights in their evaluations of uncertain future outcomes. The paper concludes with theoretical and practical implications of the new behavioral option value model and the empirical findings.


Keywords: Product Set Choice, Option Value, Consumer Decision Making, Behavioral Economics, Future Consumption.

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Consumers often purchase a product not for immediate use, but for use at some time in the future. For example, consumers book an airline ticket to go on a holiday that they will undertake a few months later, or they close a health insurance for use in case of a future accident. Such forward buying decisions are relatively straightforward if consumers already exactly know the utility they will obtain from the product at the future time of consumption. They can then evaluate each product based on its (known) future utility and make a decision accordingly. However, often, the utility of a product in the future is uncertain. There are situational factors outside of the consumer's control that can affect the product's utility, while the realization of these factors in the future is not yet known to consumers. For example, when choosing a health insurance, the consumer's future health condition is uncertain, and therefore the future utility of coverage by the insurance is also uncertain.

Consumers can handle this type of uncertainty by introducing flexibility in the choices that they make (Anderson, Hansen, and Simester 2009; Guo 2006, 2010; Kreps 1979; Sainam, Balasubramanian, and Bayus 2010; Walsh 1995). Research shows that consumers select greater variety and a smaller share of their favorite products for future consumption than for immediate use (Read and Loewenstein 1995; Simonson 1990). Consumers also incorporate flexibility in their subjective evaluation of sets of alternatives (Shin and Ariely 2004) and are willing to sacrifice expected utility to preserve flexibility for the future (Bown, Read, and Summers 2003).

Real option theory formalizes this value of choice flexibility that occurs when moving from a one-stage, single alternative, decision making process at the current time, to a two-stage set-based decision process that provides flexibility by allowing one to make decisions both at the current and the future time (Trigeorgis 1993). More specifically, real option value represents the
value to the decision-maker of being able to postpone a final, single alternative decision to a later stage when more information is revealed (Gollier and Trench 2003). To illustrate real option value from a consumer decision making perspective, consider a consumer's choice between health insurance networks, a societally highly relevant consumer decision (Wedig 2013). Health insurance networks typically compete on the extent of coverage of healthcare facilities that they include, and these facilities may differ in terms of quality and treatment specialization (Ericson and Starc 2015; Harris, Schultz, and Feldman 2002). Consumer option value then arises when consumers initially select a network with greater coverage because this allows them to choose a more fitting healthcare facility when an unforeseen future medical condition arises later. Conversely, when initially a more restricted network is selected, the consumer may no longer be able to select the best fitting healthcare facility in the future. Thus, depending on the specific 'state of the world' that arises in the future, the utility of a healthcare facility differs, and the option of being able to choose from a large set of alternatives (versus being forced to select one from a more restricted set of alternatives) can be valuable.

Firms can respond to consumer preferences for this type of flexibility by offering consumers the possibility of selecting a product at a later time. For example, travel firms can allow consumers to cancel a flight or hotel room booking at a later time, or sports event organizers can offer consumers a refund for a sports final ticket when their favorite team is not playing (Sainam, Balasubramanian, and Bayus 2010). In our paper, we examine another prominent type of option value that firms can offer to consumers when future consumption utility is uncertain, which is to allow consumers to initially choose between different sets of products, from which they can then choose a single most preferred product in the future (Kahn and

Lehmann 1991). This is the case, for example, when consumers choose between health insurance networks that vary in the extent to which they cover different healthcare services and from which they will only later use a medical service in case of an unforeseen illness or accident. As another example, when choosing a university, depending on which program they start, students will have access to different (elective) courses and timing pathways that they can choose from later on in their studies. Similarly, different gym memberships in one's home city may provide different levels of access to different gyms in other cities when travelling for work.

The first contribution of this paper is to develop a formal utility model of consumers' valuation of the additional decision flexibility provided by product sets with option value, compared to having to make an immediate product choice (from these same sets). Current models of consumer product set choices for future consumption have addressed the case where an entire set of products is consumed in the future (Dubé 2004; Guo 2006; Kim, Allenby, and Rossi 2002; Walsh 1995). However, these set choices do not reflect the option value case where initially a product set is selected, and only later consumers choose what is the best alternative at the time of consumption. To analyze this latter type of decision, we formulate a normative model of consumer product set choice that is rooted in real option theory. The model allows us to formally distinguish the expected utility of the single product one would choose from the set now (what we call the immediate expected utility of the product set), from the utility gain from having the flexibility to postpone the final product choice from the set until the future (what we call the option value of the product set). This option value arises from variation in the consumption utility of the alternatives in each of the - currently uncertain - possible future 'states of the world' that a consumer may face.

Second, we extend this normative model of consumers' option value evaluations with two behavioral aspects. The first behavioral extension is behavioral option value weighting. Research shows that consumers could overvalue the flexibility offered by real options, as this flexibility ensures that they stay in control and can adapt to future events (Shin and Ariely 2004). However, cognitively evaluating the value of future flexibility also requires a complex mental process in which consumers simulate the choices they can make in different possible future states of the world. The complexity of this mental process suggests an alternative view, which is that consumers could also underweight the flexibility provided by real options, if they simplify their decision making by attaching lower weight to more complex components (Dellaert, Donkers, and Van Soest 2012; Swait and Adamowicz 2001). We account for these possible effects in option value weighting in our behavioral model. The second behavioral extension we introduce is that we incorporate the possibility that consumers apply subjective decision weights in their option value evaluations that replace the known probabilities of possible future states of the world when combining and weighting the corresponding outcomes by each state (Kahneman and Tversky 1979; Tversky and Wakker 1995). This second behavioral aspect is likely to affect consumer product set choices because option value, by definition, depends on the uncertainty of different future outcomes and decision weights impact consumer decisions in many other areas of decision making under uncertainty (Fischhoff and Broomell 2020; Gao, Frejinger and Ben-Akiva, 2010; Heiman et al. 2015).

Third, our research proposes and demonstrates a choice experiment-based decision elicitation and econometric modeling method that allows marketing researchers and managers to estimate consumers' behavioral option value for sets of alternatives. The proposed approach
provides option value estimates that allow for comparisons between consumer valuations of different flexible sets for future product choices to be offered to consumers. Such comparisons can guide firms in selecting product sets that help consumers overcome uncertainty in future consumption in a cost-effective manner.

In the remainder of the paper, we first theoretically derive the proposed normative and behavioral option value models of consumer product set choice. Next, we outline the new threestage method that combines experimental decision elicitation and econometric modeling to allow for the estimation of the models. Then, the results from four experiments that test and illustrate the proposed theory and method are presented. The results provide clear support for our theorizing. They demonstrate firstly, that, as predicted, consumers take into account option value when selecting product sets from which to choose an alternative in the future. Secondly, the results also provide support for the two proposed behavioral extensions. They show that consumers subjectively overweigh option value and apply behavioral decision weights in their evaluations of different future states of the world as predicted. The paper concludes with a discussion of theoretical and practical implications of the behavioral option value model and our findings.

## THEORY

A normative option value model of consumer product set choice
Normative real option value theory was originally developed in financial economics to capture the value of investment decision flexibility, which had been neglected in classic investment evaluation models. Traditional investment evaluation methods largely ignored the possibility of altering or even abandoning a project depending on changes in the market
(Trigeorgis 1993). By taking a sequential decision making approach, real options allow one to pay for the option to reconsider an earlier decision at different points in time in the decisionmaking process (Gollier and Treich 2003). Subsequently, in strategic management, firms also have utilized real option reasoning in making project investment decisions (Gunther McGrath and Nerkar 2004).

In marketing, real option analysis has mainly found its way into the literature via research in marketing strategy and customer lifetime value (CLV) analysis. The potential actions in a dynamic relationship between a buyer and a seller (e.g., continuation or ending the relationship at different moments in time) can be viewed as a set of options for both the seller and the customer (Levett et al., 1999). Including option value in CLV can considerably affect firms' valuations of different customers (Haenlein, Kaplan, and Schoder 2006). More recently, Sainam et al. (2010) proposed an option value-based pricing mechanism based for offering consumers the possibility to pay more for having the option to decide to use a product (or not) at a later time (i.e., a sports final ticket depending on if your favorite team is playing). From a consumer perspective, marketing research has shown that as a general feature, consumers value flexibility in sets (Bes et al., 2017; Kahn and Lehman 1991, Shin and Ariely 2004). However, at a more detailed level, if, and if so, how, consumers' evaluations of flexibility reflect theoretical option value is not clear.

We propose and test a utility model of how consumers evaluate option value. In particular, we address the option value that arises when future consumption utility is uncertain, and consumers can initially choose between different sets of products from which they can then select one product in the future - after the initial uncertainty is resolved. Consumers who choose a product set from which to select a product in the future, maximize their expected utility,
knowing that their most preferred alternative in each set might vary depending on the future consumption context, i.e., across possible future states of the world (Belk 1975; Guo 2006; Kahn and Lehmann 1991; Sainam et al. 2010; Simonson 1990; Walsh 1995). Therefore, when products provide utility that is (future) context dependent, consumers should account for the option value provided by the flexibility of future choices.

Theoretically, to define consumer option value, we decompose the utility value of selecting a flexible set of products from which a final product choice can be made in the future into two components: 1) The expected utility of the single product one would choose now, when making an immediate choice of an alternative for future consumption, with uncertainty about which future state of the world may occur. We refer to this component as the immediate expected utility of the product set, and 2) The utility gain from having the flexibility to postpone the final product choice from the set until the future, after the new state of the world is revealed to the consumer. This second component constitutes what we call the option value of the product set.

To formalize these two utility components, consider a consumer $i$ who plans to consume a product at a future point in time. The utility of different products at that point in time depends on the states of the world that can occur at that time (i.e., the different consumption contexts that may arise) and it is uncertain which state of the world will materialize. Let $J$ be the set of all products available in the market, let $j \in J$ represent a single product, and $F$ be the set of all possible future states $f \in F$ of the world, then $V_{j f}$ is the utility of product $j$ when the future state of the world $f$ occurs ${ }^{1}$.

[^0]To provide consumers with flexibility in their selection of a final product in the future, firms offer consumers product sets $s$ containing different products $j$ (with each $s$ a subset from $J$ ). Consumers first choose a product set and then choose the best available product in their selected set later, when they know which future state has become a reality. The utility of the best available product in set $s$ depends on which future state $f$ materialized and is expressed as $\max _{j \in s} V_{j f}$. Let $P_{f}$ be the probability that a future state $f$ occurs. Then, the utility of a set $s$ for which the consumer has the opportunity to flexibly make a final product selection later $\left(V_{s}^{\text {Flexible }}\right)$ is the probability-weighted sum (for the occurrence of each future state) over the utilities of the best available product in that set in each future state $f$ :
(1) $V_{s}^{\text {Flexible }}=\sum_{f \in F} P_{f} * \max _{j \in s} V_{j f}$

Next, to express the option value of a set, we compare the utility of a set when the final product selection can be made later, to that set's utility when the consumer has to select an alternative from the set immediately. For this purpose, we define the immediate expected utility ( $V_{s}^{\text {Immediate }}$ ) of set $s$. This immediate utility expresses the set's value when the consumer needs to choose a single alternative now, without knowing which future state materializes. The immediate utility is determined by the utility of the product in the set with the highest expected utility based on the product's utility in each future state of the world times the probability $P_{f}$ of that future state occurring. This is expressed as:
(2) $V_{s}^{\text {Immediate }}=\max _{j \in s}\left\{\sum_{f \in F} P_{f} * V_{j f}\right\}$

Then, the option value ( $V_{s}^{\text {option }}$ ) of set $s$ is defined as the additional utility to the consumer that arises from being able to postpone the final product choice until after the future state is known. In other words, option value reflects the incremental value of choosing an alternative based on knowledge about which future state has materialized. This additional value is determined by the
difference between the total utility of the set when being able to flexibly make a decision later $\left(V_{s}^{\text {Flexible }}\right)$ and the set's immediate expected utility $\left(V_{s}^{\text {Immediate }}\right)$ :
(3) $V_{s}^{\text {Option }}=V_{s}^{\text {Flexible }}-V_{s}^{\text {Immediate }}$

Or, in other words, and after reordering, the utility of choosing a product set from which a final product choice can flexibly be made later, is the sum of a set's immediate expected utility and the set's option value:
(4) $V_{s}^{\text {Flexible }}=V_{s}^{\text {Immediate }}+V_{s}^{\text {Option }}$

## Behavioral model of product set choice

Normatively, when choosing between product sets that allow them to make their final product decision later, in their set evaluations, individuals should weigh the immediate expected utility and option value components equally since both are directly expressed in terms of the consumer's utility (i.e., they are expressed in the same 'unit'). However, behaviorally, there may be differences in the weight consumers attach to these two components. On the one hand, complexity in decisions can lead consumers to make use of simplifying heuristics and attach less weight to specific aspects of a decision, where more elaborate, more complex components may be more likely to be ignored than relatively simpler ones (Dellaert, Donkers, and Van Soest 2012; Payne, Payne, Bettman and Johnson 1993; Swait and Adamowicz 2001). Therefore, the complexity of the option valuation process could result in consumers' underweighting of the option value in product set choice. On the other hand, there is also evidence that the use of simplifying heuristics can lead consumers to overvalue the value of flexibility as a more general positive aspect of a product set (Shin and Ariely 2004). In the latter case, consumers may overweight the option value component relative to the immediate expected utility. Thus, it is not
clear upfront if consumers will under- or overweigh option value utility relative to immediate expected utility.

To test for these potential behavioral effects, we introduce a first behavioral aspect in the normative option model. This behavioral aspect captures the relative importance of the option utility component compared to the immediate expected utility component in the consumers' set valuation. More specifically, we introduce an additional parameter $\gamma$, that captures the relative weight of the option value versus the immediate expected utility component. This gives the following behavioral option value model:
(5) $V_{s}^{\text {B.Flexible }}=V_{s}^{\text {B.Immediate }}+\gamma V_{s}^{\text {B.Option }}$
where, $V_{s}^{\text {B.Flexible }}, V_{s}^{\text {B.Immediate }}$, and $V_{s}^{\text {B.Option }}$ are behavioral utility components. The normative option value model corresponds to the case where $\gamma=1$ and where the behavioral utility components are defined as the corresponding normative utility components from equations 1 and 2.

As a second behavioral extension, we predict that in evaluating the utility of a product set consumers can attach decision weights to the occurrence of future events that deviate from the objective probabilities that they occur (Bleichrodt and Pinto 2000; DeLisle, Diamantopoulos, Fodor, and Krieger 2017; Huang, Burris, and Shaw, 2017; Kahneman and Tversky, 1979). In line with prospect theory, we formalize the resulting biases in the evaluation of uncertain outcomes by transforming the objective probabilities $P_{f}$ of the future states f into behavioral decision weights $\pi_{f}$ (Donkers, Melenberg and Van Soest, 2001; Kahneman and Tversky, 1979). The overall value of a probabilistic alternative is then given by the sum of the utility values of the outcomes multiplied by the decision weights associated with these outcomes. Accordingly, we
extend the behavioral option value model (eq. 5) using the following two behavioral expressions that replace the objective probabilities by decision weights:
(6) $\left.V_{s}^{\text {B.Immediate }}=\max _{j \in s}\left\{\sum_{f \in F} \pi_{f} * V_{j f}\right)\right\}$
(7) $\left.V_{s}^{\text {B.Option }}=\sum_{f \in F} \pi_{f} * \max _{j \in s}\left\{V_{j f}\right\}-\max _{j \in s}\left\{\sum_{f \in F} \pi_{f} * V_{j f}\right)\right\}$

## THREE-STAGE CHOICE EXPERIMENT APPROACH AND ECONOMETRIC MODEL

To estimate and test the proposed behavioral option value model, we introduce a combination of a three-stage choice experiment approach and econometric model that allows for the identification of the different components in the theory.

## Experimental Approach

The three-stage choice experiment approach encompasses multiple within-subject choice experiments. Choice experiments are commonly used to measure consumer preferences for goods and services across a wide variety of domains and have been recognized as one of the areas where marketing research has had the strongest impact on marketing practice (Louviere, Hensher, and Swait 2000; Roberts, Kayande, and Stremersch 2014). Earlier choice experimentbased research has supported the identification and estimation of complex consumer decisions by disentangling these decisions in sub-tasks, that cover part of the decision that are well-identified and less complex and that are subsequently integrated in a joint estimation process (Louviere et al. 2000; Oppewal, Louviere and Timmermans 1994). Such a multi-stage experimental approach facilitates identification while also managing the complexity of the response for participants.

We adapt this approach to the context of consumer product set choices with option value. In particular, different experiment stages are introduced that separate choices given different possible states of the world and choices with uncertainty regarding these states of the world.

Jointly, these stages allow for identification of the consumers' option value preferences in product set choices. More specifically, the approach can be summarized as follows (see Table 1): Stage 1 addresses the case in which each set contains only one product and the future state of the world is known. Stage 2 addresses the case in which each set also contains only one product but the future state of the world is uncertain. Stage 3, finally, addresses the case where consumers choose between sets that contain multiple products and the future state of the world is uncertain.

Stage 1 - In the first stage of the experimental approach, consumers' product utilities $\left(V_{j f}\right)$ are identified separately for each of the possible future states $f$. In a series of choice experiment tasks, with each task concerning one of the different future states, consumers are presented with one future state and are asked to make choices given that this state has become the reality that they face. This is done for the case in which each set contains only one product. The presentation order of the future states is counterbalanced over participants.

Stage 2 - In the second stage, consumers' expected immediate utilities ( $\left.V_{s}^{\text {B.Immediate }}\right)$ are identified. More specifically, consumers are presented with the probabilities at which each future state will occur and choose between different products for consumption in the future. This is done for the case in which each set contains only one product. Because there is only a single product to be selected, there is no option value, and the alternative with the highest expected utility will be chosen. This second stage allows for identification of the behavioral decision weights $\left(\pi_{f}\right)$. Contrary to stage 1 , in the second stage, there is only one choice experiment task as all future states are relevant for each product choice.

Stage 3 - In stage 3, identification of the option value is achieved. Like in stage 2, in this choice experiment, consumers are presented with probabilities at which each future state will occur, but now with their task is to choose between different sets containing multiple products.

This structure allows for the estimation of $V_{s}^{\text {B.Flexible }}$. In particular, since consumers' utilities $\left(V_{j f}\right)$ and their immediate expected utilities $V_{j}^{\text {B.Immediate }}$ including $\pi_{f}$, were already identified from Stages 1 and 2, the current Stage 3 allows for identification of $\gamma$, the weight of the option value in the consumers' set evaluation.

Table 1: Overview of the Experiments

|  | Number of <br> options in <br> the set | Outcome of the future states | Objective probabilities of the <br> future states |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Experiments <br> 1,3 and 4 | Experiment 2 | Experiment <br> 1,2 and 3 | Experiment 4 |
| Stage 1a | 1 | $5(25)$ Sessions ${ }^{\mathfrak{t}}$ | $1(99)$ Sessions | NA | NA |
| Stage 1b | 1 | $25(5)$ Sessions | $99(1)$ Sessions | NA | NA |
| Stage 2 | 1 | 5,25 Session | 1,99 Session |  |  |
| Stage 3 | 3 | 5,25 Session | 1,99 Session |  | $10 \% / 90 \%$ |

${ }^{£}$ With counterbalancing between 5 and 25 sessions in stage 1a and 1 b

## Econometric Model

In the econometric model estimation, we apply a logit specification with heterogeneous preferences to model consumers' set choices across all stages. We take into account heterogeneity in consumers' preferences by allowing the utility weights of the product attributes to vary across individuals.

First, we define the utility for consumer $i$ of product $j$ in future state $f$ as:
(8) $V_{i j f}=\mathbf{X}_{\mathrm{j}}{ }^{\prime} \boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{f}}$
where, $\mathbf{X}_{\mathbf{j}}$ is a vector of attributes that defines product $j$ and $\boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{f}}$ is a vector of individual $i$ 's future state-dependent preferences for these attributes. We assume a joint normal distribution for individuals' attribute utility weights:
(9) $\left(\boldsymbol{\beta}_{i}^{f=1}, \ldots, \boldsymbol{\beta}_{\boldsymbol{i}}^{\boldsymbol{f}=\boldsymbol{F}}\right) \sim N(\beta, \Sigma)$.

These individual-level future-state specific valuations of a product define the set-level valuations outlined in equations 6 and 7 .

Next, the resulting individual-specific set valuations drive participants' choices between the sets in each task type, which we model with a logit model as follows. Let $t$ denote the different tasks in the experimental approach, then the utility of a product set is:
(10) $U_{i s t}=V_{i s}^{B . F l e x i b l e}+\varepsilon_{i s t}$
where, $V_{i s}^{\text {B.Flexible }}$ is defined in equation 5 and the error terms $\varepsilon_{i s t}$ are independently and identically Gumbel distributed with scale $\mu_{t}$. Note that we allow for the scale of the error term $\mu_{t}$ to differ across different types of tasks in the experiment's stages to account for differences in decision complexity in the different tasks (Dellaert, Donkers, and Van Soest, 2012). The three experimental stages as well as all but one of the different future states within stage 1 are embedded with their own scale parameter. For identification, we fix the scale of the utilities by setting the error scale equal to 1 for the first of the choice experiment task types.

In the experimental approach, consumers make multiple choices in each choice experiment task. Let $S_{k t}$ be the set of the product sets available to the consumer in choice $k$ in task $t$. Then, the probability that consumer $i$ chooses set $s$ in choice $k$, given their preference weights $\beta_{i}$, is given by:

$$
\begin{equation*}
P_{i s k t}=\frac{e^{\mu_{t} V_{i s}^{B . F l e x i b l e}}}{\sum_{s^{\prime} \in S_{k t}} e^{\mu_{t} V_{i s \prime^{\prime}}^{B . F l e x i b l e}}} \tag{11}
\end{equation*}
$$

Integrating out the heterogeneity distribution in equation (9) across all the choices in the different task types results in the following log-likelihood:

$$
\begin{equation*}
L L\left(y_{i} \mid \beta, \Sigma, \gamma, \pi\right)=\log \int\left[\prod_{k t} P_{i s k t}\right] f\left(\beta_{i} \mid \beta, \Sigma\right) d \beta_{i} \tag{12}
\end{equation*}
$$

Since the integral in equation (12) cannot be calculated analytically (Revelt and Train, 1998; Guo, 2010), the simulated maximum likelihood method is employed to approximate the loglikelihood function.

## OVERVIEW OF EXPERIMENTS

Four experiments were conducted to test the theorizing. The experiments focus on the societally relevant topic of consumer choices between different healthcare plans offered by health insurance providers. Healthcare plan choices have strong implications for consumer welfare. Recent developments in the U.S. and elsewhere have greatly increased the opportunity (and corresponding decision-making burden) for consumers to make their own health insurance decisions (Bhargava, Loewenstein, and Sydnor 2017; Ericson and Starc 2012). A challenge in making good health insurance plan decisions is that the plans typically offer different levels of coverage in terms of the healthcare providers a consumer can use (i.e., a plan may offer limited coverage versus full coverage). The level of network coverage is an important determinant of consumer decision making in health insurance (Dafny, Hendel, and Wilson 2015; Ericson and Starc 2015), and the experiments in this paper address the importance of the option value resulting from differences in healthcare plan network coverage.

Experiments 1 and 2 introduce the estimation of option value and the first behavioral component: the impact of behavioral option value weighting in consumers' product set choices. To control for possible differences in decision weights (the second behavioral component) in these experiments, the health product sets differ in composition, but the probabilities of the
different future states are equal. In the experiments, participants are presented with physical therapy clinics that are more versus less attractive depending on the individual's (uncertain) future need for treatment. The results of the two experiments provide support for both the predicted impact of option value on consumer product set choices with uncertain future consumption and the hypothesis that consumers behaviorally weigh this option value in their decisions. Experiment 3 introduces decision weights as the second behavioral aspect of the proposed option value model. The experiment also provides a robustness check of the results of Experiments 1 and 2. To do so, it includes an additional attribute in the consumer product set choice (price) which is valued independently of the future state of the world (i.e., the utility weights for the price component are the same in all future states). The results show that with equal probabilities (as in Experiments 1 and 2), decision weights do not deviate from the objective values. Finally, Experiment 4 further investigates decision weights by introducing differences in the probabilities at which future states occur. This additional experimental manipulation allowed for the estimation of decision weights along with behavioral option value weights without the need for a common fixed attribute across the different stages (as in Experiment 3). The results replicate the findings from the earlier experiments and show that, as predicted, behavioral decision weights more accurately describe consumers' option value evaluations than objective probabilities when probabilities vary between future states. The data and analysis syntax for all four studies are available at https://osf.io/qnbf3/?view only=e1725f654d5d43dcb601170ed7d7e114.

## EXPERIMENT 1: CONSUMERS' BEHAVIORAL OPTION VALUE WEIGHTING

Experiment 1 was designed to test the impact of option value on consumers' product set choices in general and behavioral option value weighting in particular. Participants were asked to
imagine that they were selecting a health insurance for the following year and that they already knew that they would need physical therapy treatment within the next three months. They were informed that different health insurance providers offered different networks of physical therapy clinics. Their task was to select their preferred health insurance provider.

## Method and data

In the experiment, the physical therapy clinics within the health insurance networks were described in terms of two attributes: an independent quality evaluation of each clinic and the distance to the clinic from the participant's home (in minutes by car). Quality varied from 6 to 9 (7 levels with increments of 0.5 , where 1 indicates very poor quality and 10 indicates very high quality), and distance from home in minutes by car from 5 to 35 minutes ( 7 levels). These attributes are shown to be important determinants of consumers' healthcare clinic choices in past research (Liu, Kong, and de Bekker-Grob 2019; Zhu, et al. 2019). Participants were informed that for their health condition requiring physical therapy, two medical severity levels were possible that were equally likely to occur. However, their medical doctor did not yet know which level of severity applied to their case. Each medical severity level corresponded to a different number of physical therapy sessions required ( 5 versus 25 treatment sessions required).

In stages $1 \mathrm{a}, 1 \mathrm{~b}$ and 2, we generated a full factorial combination of the clinics (Louviere at al. 2000). In each choice task, two clinics were randomly selected from the full set of combinations with the added restriction that uninformative choice tasks, where one clinic dominated the other (was better in all attributes), were automatically removed. In stage 3 , we generated a full factorial combination of the clinics and randomly selected six clinics (three per set). In this stage, to remove uninformative choice tasks, firstly, we eliminated sets in which one clinic dominated one of the other two clinics and ,secondly, we removed choice tasks in which
one set dominated the other (i.e., tasks in which all the clinics in one set were worse than the clinics in the other set). For each task in each stage of the experimental approach, 10 choice sets were randomly assigned to each participant for a total 882 choice sets in stages 1 and 2 and 11781 in stage 3. In each choice set, participants were asked to select the health insurance provider they preferred based on the insurance provider's network, an opt-out option was not available.

A total of 400 participants who resided in the USA were recruited through MTurk to complete the experiment for a payment of $\$ 3$ per person. After elimination of two responses due to incomplete submission, 398 valid responses were obtained. The average age of the participants was 33 years old and $41 \%$ of them identified as women. Of the participants, $88 \%$ had a health insurance provider and $43 \%$ had previous experience with physical therapy treatment.

## Results

The results of experiment 1 show that participants preferred higher treatment quality and shorter travel distance as expected. Depending on the future state, participants' valuation of the attributes also shifted in the expected direction, with quality having a more positive $\left(\beta_{\text {quality }}^{5}=\right.$ 2.827 vs. $\left.\beta_{\text {quality }}^{25}=3.684\right)$ and travel distance having a more negative $\left(\beta_{\text {distance }}^{5}=-.169\right.$ vs. $\left.\beta_{\text {distance }}^{25}=-.270\right)$ impact on consumers' choices as the number of treatments needed increases from 5 to 25 .

The estimation results (see Table 2) provide support for the hypothesized effect of option value on consumers' product set choices for future consumption. They show that consumers account for the uncertain future state of the world conditions by attaching positive utility to the real option value of being able to postpone their product choice ( $\gamma=3.924, \mathrm{p}<.001$ ).

Interestingly, the behavioral effect of option value $(\gamma)$ is larger than 1 , which implies that in this context, option value is overvalued by participants compared to the normative model.

To evaluate the overall impact of option value, we also compared the model's loglikelihood and BIC with that of a model without option value $(\gamma=0)$ as well as that of a normative model with gamma fixed to one $(\gamma=1)$. The results (see Table 3 ) show that the proposed behavioral model has the highest loglikelihood and lowest BIC values and therefore the best model fit.

## Table 2: Parameter Estimates Experiment $1^{\text {a }}$

| Parameter | Estimate | SE |
| :---: | :---: | :---: |
| $\beta_{\text {quality }}^{5}$ | 2.827 *** | . 145 |
| s.d. $\beta_{\text {quality }}{ }^{2}$ | 2.503 *** | . $155^{3}$ |
| $\beta_{\text {distance }}^{5}$ | -. 169 *** | . 009 |
| s.d. $\beta_{\text {distance }}$ | . 266 *** | . 042 |
| $\beta_{\text {quality }}^{25}$ | $3.684 * * *$ | . 536 |
| s.d. $\beta_{\text {quality }}^{25}$ | 3.015 *** | . 421 |
| $\beta_{\text {distance }}^{25}$ | -.270 *** | . 039 |
| s.d. $\beta_{\text {distance }}^{25}$ | . 968 *** | . 024 |
| Option value weight $(\gamma)^{\text {£ }}$ | 3.924 *** | . 788 |
| Scale factor stage $1 \mathrm{a}\left(\mu_{1 \mathrm{a}}\right)$ (5 sessions) | Fixed to 1 |  |
| Scale factor stage 1 b ( $\mu_{1 \mathrm{~b}}$ ) (25 sessions) | . 691 *** | . 104 |
| Scale factor stage $2\left(\mu_{2}\right)$ | . 861 *** | . 086 |
| Scale factor stage $3\left(\mu_{3}\right)$ | . 408 *** | . 040 |

[^1]```
a Random coefficients covariances not included in the table for clarity.
Signif.: ***:<.001, **: <.01, *: <. }0
E Tested against 1
```

Table

## Model Fit Comparison Experiment 1

| Model | Loglikelihood | BIC |
| :---: | :---: | :---: |
|  |  |  |
| proposed behavioral model | -7046.16 | 14200.07 |
| $\gamma=0$ (no option value) | -7058.10 | 14217.97 |
| $\gamma=1$ (normative model) | -7053.93 | 14209.63 |

## Discussion

The results of experiment 1 provide support for the hypothesized effect of option value (i.e., valuing flexibility) on consumers' set evaluation for future consumption. Option value, in addition to the expected utility of the set, contributes to the set utility. This is in line with the hypothesis that consumers value the flexibility that a set of products can offer them.

Interestingly, the estimated behavioral weight of option value $(\gamma)$ is greater than 1 , which implies that consumers not only take option value into account but also tend to overvalue option value in this case.

## EXPERIMENT 2: BEHAVIORAL OPTION VALUE WEIGHTING WITH MORE DIFFERENT FUTURE STATES OF THE WORLD

Experiment 2 replicated the settings from experiment 1 with one exception, which was that the difference between the outcomes of the future states of the world was made to vary more
strongly. We anticipated that a greater divergence in future states of the world would further increase option value to consumers.

## Method and Data

The experimental setting was identical to that experiment 1 , with the exception of the number of possible physical therapy sessions that would be required in the two medical conditions. This number was varied more strongly and differed between 1 and 99 sessions. As in experiment 1 , in each stage of the experimental approach, 10 choice sets were randomly assigned to each participant of a total of 882 choice sets in stages 1 and 2 and 11781 in stage 3 .

A total of 400 participants who resided in the USA were recruited through MTurk to complete the experiment for a payment of $\$ 3$ per person. After elimination of 1 response due to incomplete submission, 399 valid responses were obtained. The average age of the participants was 31 , and $42 \%$ of them identified as women. $88 \%$ of the participants had a health insurance provider, and $41 \%$ of them had experience with physical therapy service.

## Results

As in experiment 1 , the results show that participants preferred higher treatment quality and shorter travel distance (see Table 4). Depending on the future state of the world, their valuation of the attributes shifted in the expected direction, with greater quality becoming more positive $\left(\beta_{\text {quality }}^{1}=3.116\right.$ vs. $\left.\beta_{\text {quality }}^{99}=20.365\right)$ and greater travel distance becoming more negative $\left(\beta_{\text {distance }}^{1}=-.175\right.$ vs. $\left.\beta_{\text {distance }}^{99}=-1.489\right)$ as the number of treatments increased from 1 to 99 . As expected, the difference in utility between the two future states of the world in experiment 2 is greater than in experiment 1 as the greater difference in number of treatments strengthens the impact.

The results of experiment 2 provide further support for the hypothesized effect of option value on consumers' product set choices for future consumption. The results show that consumers value the option value of being able to postpone their product choice and option value significantly contributes to the set utility $(\gamma=5.981, \mathrm{p}<.001)$. As in experiment 1 , the estimate for the behavioral effect of option value $(\gamma)$ is larger than 1 , which shows that option value is overvalued compared to the normative model.

Table 4: Parameter Estimates Experiment 2 ${ }^{\text {a }}$

| Parameter | Estimate | SE |
| :--- | :---: | :---: |
| $\beta_{\text {quality }}^{1}$ | $3.116^{* * *}$ | .145 |
| s.d. $\beta_{\text {quality }}^{1}$ | $2.081^{* * *}$ | .124 |
| $\beta_{\text {distance }}^{1}$ | $-.175^{* * *}$ | .010 |
| s.d. $\beta_{\text {distance }}^{1}$ | $.135 * * *$ | .017 |
| $\beta_{\text {quality }}^{99}$ | $20.365^{* * *}$ | 5.503 |
| s.d. $\beta_{\text {quality }}^{99}$ | $15.068^{* * *}$ | 4.133 |
| $\beta_{\text {distance }}^{99}$ | $-1.489 * * *$ | .396 |
| s.d. $\beta_{\text {distance }}^{99}$ | $1.480 * * *$ | .014 |
| Option value weight $(\gamma)^{£}$ | $5.981 * * *$ | 1.822 |
| Scale factor stage 1a $\left(\mu_{\mathrm{la}}\right)(5$ | Fixed to 1 |  |
| sessions $)$ |  |  |
| Scale factor stage 1b $\left(\mu_{1 \mathrm{~b}}\right)(25$ | $.129 * * *$ | .035 |
| sessions $)$ |  |  |
| Scale factor stage $2\left(\mu_{2}\right)$ | $.250 * * *$ | .060 |
| Scale factor stage 3 $\left(\mu_{3}\right)$ | $.108^{* * *}$ | .026 |

a Random coefficients covariances not included in the table for clarity. Signif.: ${ }^{* * *}:<.001, * *:<.01, *:<.05$
${ }^{£}$ Tested against 1

We also compared the loglikelihood and BIC of the proposed model with the model without option value $(\gamma=0)$ and the normative model where gamma is fixed to one $(\gamma=1)$. The results (see Table 5) show that the proposed model has the highest loglikelihood and lowest BIC values and thus the best model fit.

Table 5: Model Fit Comparison Experiment 2

| Model | Loglikelihood | BIC |
| :--- | :---: | :---: |
| Proposed behavioral model | -7117.57 | 14342.93 |
| $\gamma=0$ (no option value) | -7124.64 | 14351.09 |
| $\gamma=1$ (normative model) | -7122.56 | 14346.92 |

## Discussion

The results of experiment 2 replicate and further support that, as predicted, in choosing product sets for uncertain future consumption, consumers attach utility to the option value of a set. As in experiment 1 , the results showed that the impact of option value is significant and that its value is behaviorally over-weighted in the context of healthcare insurance networks.

## EXPERIMENT 3: INTRODUCING BEHAVIORAL DECISION WEIGHTS

Experiment 3 introduced decision weights as the second behavioral aspect of the proposed option value model. This experiment replicated the setting of Experiment 1, with one exception which was that it included an additional attribute in the consumer product set choice (price) which is valued independently of the future state of the world. Observing consumers' set
choices including this attribute allows for identification of decision weights even when probabilities of future states are fixed.

## Method and data

The structure of experiment 1 was replicated with the exception that the physical therapy clinics were described with one additional attribute, intake fee, whose value was independent of the number of sessions a consumer would have to attend. As in experiment 1 , the other two components of the experimental conditions that were varied were the number of physical therapy sessions required 5 and 25 sessions and the number of clinics in the network. More specifically, in each choice task, the physical therapy clinics were presented by the three attributes, quality, distance, and intake fee. Quality varied from 6 to 9 ( 7 levels with increments of 0.5 , where 1 indicates very poor quality and 10 indicates very high quality), distance from 5 to 35 minutes ( 7 levels), and intake fee was either $\$ 40, \$ 50$, or $\$ 60$, to be paid only once before the start of treatment.

An important benefit of including the additional attribute of intake fee is that it makes it is possible to identify the behavioral decision weight attached to the two equal probability conditions. In experiments 1 and 2, the utility weights for each future state were only identified up to a future-state specific scale. By assuming the weight for each future state to be identical, we ensured these scales were comparable. Now, in experiment 3 , since the utility of a specific intake fee is independent of the number of sessions needed (and assuming it is also valued independently by consumers), we can ensure utilities are measured on the same scale across each future state by restricting the utility weight for the intake fee to be the same across all experimental stages. This approach permits us to estimate stage-specific error scales and also the decision weights for each future state. In each stage of the experimental approach, 10 choice sets
were randomly assigned to each participant from a total of 12237 choice sets in stages 1 and 2 and 5049 in stage 3.

A total of 410 U.S. participants were recruited on Prolific and completed the experiment for a fixed payment ( $£ 3.75$ per person). After removing 8 responses due to incomplete submissions, a total of 402 valid responses remained. The average age of the participants was 37 , and $48 \%$ of them identified as women. $91 \%$ of the participants had health insurance and $43 \%$ had experience with physical therapy service.

## Results

In the estimation, we fixed the utility weight for the monetary value of intake fee to -1 (minus 1). This is feasible because the intake fee in the experiment was independent of the number of sessions. As a result, all other utility weights are estimated in relation to this fixed value and can be interpreted as participants' willingness to pay for each of the other attributes (Sonnier, Ainslie and Otter 2007; Train and Weeks 2005). Depending on the future state, participants' valuation of the attributes shifted in the expected direction, with quality having a more positive $\left(\beta_{\text {quality }}^{5}=28.856\right.$ vs. $\left.\beta_{\text {quality }}^{25}=35.269\right)$ and travel distance having a more negative $\left(\beta_{\text {distance }}^{5}=-1.772\right.$ vs. $\left.\beta_{\text {distance }}^{25}=-2.537\right)$ impact on consumers' choices as the number of treatments needed increases from 5 to 25 . The results also show that, as before, option value is over-weighted by participants ( $\gamma=8.137, \mathrm{p}<.001$ ). The decision weight does not differ significantly from the objective probability of .5 of the future states (Decision weight $=.501, \mathrm{p}=$ .215). Estimation results are reported in Table 6.

To evaluate the goodness of fit of the proposed model, we compared the loglikelihood and BIC of this model with a model without option value $(\gamma=0)$ and with a normative model $(\gamma$
$=1$ ). The results (see Table 7) show that the proposed behavioral model has the lowest loglikelihood and BIC and therefore has the best model fit.

Table 6: Parameter Estimates Experiment 3a

| Variable | Coef. | SE |
| :---: | :---: | :---: |
| $\boldsymbol{\beta}_{\text {quality }}^{5}$ | 28.856 *** | 1.069 |
| s.d. $\boldsymbol{\beta}_{\text {quality }}$ | 17.884 *** | . 889 |
| $\boldsymbol{\beta}_{\text {distance }}{ }^{\text {b }}$ | $-1.772 * * *$ | . 070 |
| s.d. $\boldsymbol{\beta}_{\text {distance }}^{\mathbf{5}}$ | . 855 *** | . 045 |
| $\boldsymbol{\beta}_{\text {quality }}^{25}$ | 35.269 *** | 1.510 |
| s.d. $\boldsymbol{\beta}_{\text {quality }}^{\mathbf{2 5}}$ | 22.018 *** | 1.230 |
| $\boldsymbol{\beta}_{\text {distance }}^{25}$ | $-2.537 * * *$ | . 118 |
| s.d. $\boldsymbol{\beta}_{\text {distance }}^{25}$ | 1.741 *** | . 082 |
| $\boldsymbol{\beta}_{\text {intake-fee }}$ | Fixed to -1 |  |
| Option value weight $(\gamma)^{\mathfrak{L}}$ | $8.137^{* * *}$ | 1.245 |
| Decision weight§ | . 501 | . 215 |
| Scale factor stage 1a ( $\mu_{1 \mathrm{a}}$ ) ( 5 sessions) | . 128 *** | . 005 |
| Scale factor stage 1 b ( $\mu_{\mathrm{lb}}$ ) ( 25 sessions) | . 092 *** | . 005 |
| Scale factor stage $2\left(\mu_{2}\right)$ | . 064 *** | . 003 |
| Scale factor stage $3\left(\mu_{3}\right)$ | . 062 *** | . 002 |
| gainst 1 <br> against .5 for equal probabilities <br> $n$ coefficients covariances not included in the table for <br> **: <.001, **: <.01, *: <. 05 |  |  |

Table 7: Model Fit Comparison Experiment 3

| Model | Loglikelihood | BIC |
| :---: | :---: | :---: |
| proposed behavioral model | -6150.69 | 12421.31 |
| Decision weight $=0.5$ | -6151.33 | 12416.60 |
| $\gamma=0$ (no option value) | -6176.85 | 12467.64 |
| $\gamma=1$ (normative model) | -6170.88 | 12455.69 |

## Discussion

Experiment 3 introduced behavioral decision weights in addition to behavioral option value weighting. The results replicate and extend the findings of experiments 1 and 2. They demonstrate that consumers attach utility to option value and even overweight the value of flexibility relative to the normative model. The results also show that the estimated decision weights are not significantly different from the normative .5 probability when both future states are equally likely to occur. This provides empirical support for the equal decision weights assumption in experiments 1 and 2.

## EXPERIMENT 4: BEHAVIORAL OPTION VALUE WITH UNEQUAL PROBABILITIES

In the first three experiments, the probabilities of future states of the world occurring were equal, and individuals applied equal decision weights to the different future states. The goal of experiment 4 was to investigate whether overweighting of option value and behavioral weighting of probability future states of the world would occur when probabilities of future states of the world differ.

## Method and data

In experiment 4, the settings from experiment 1 were repeated, except for the probabilities of the two future states, which were set at $10 \%$ and $90 \%$ instead of $50 \%$ and $50 \%$. We created two probability conditions that differed in terms of which of the two future scenarios was least likely to occur: the 5 or 25 session scenarios. We will refer to the $10 \%$ probability of 5 sessions (with $90 \%$ for 25 sessions) as condition 1, and the $10 \%$ probability of 25 sessions (with $90 \%$ for 5 sessions) as condition 2 . These two conditions were manipulated between subjects. Because the data collection for this experiment was done during the Covid-19 pandemic, respondents were asked to imagine that the pandemic had ended and that they were planning for the next year.

To introduce the different probabilities for the future states, participants were informed in stages 2 and 3 of the experimental approach that while their physician had diagnosed them with a condition that requires physical therapy treatment, the physician was in doubt between two specific conditions. In particular, in condition 1 (vs. condition 2) they were told that based on their physician's experience, of the 100 people with their symptoms, 10 (vs. 90 ) out of 100 will have a mild condition, and 90 (vs. 10) out of 100 people will have a moderate condition. As a result, the number of physical therapy sessions required was not known yet. They were informed that the mild condition required 5 sessions of physical therapy, and the moderate condition required 25 sessions of physical therapy in the next three months. As in experiment 1 and 2, in each stage of the experimental approach, 10 choice sets were randomly assigned to each participant of total 882 choice sets in stages 1 and 2 and 11781 in stage 3.

A total of 800 U.S. participants ( 400 per experimental condition) were recruited through MTurk to complete the experiment for payment (3\$ per person). Two responses were removed due to incomplete submissions and a total of 798 valid responses remained ( 399 per condition). The average age of the participants was 33 , and $44 \%$ of them identified as women. $89 \%$ of the participants had health insurance and $42 \%$ had experience with physical therapy service. Results

As in the previous experiments, depending on the future state, participants' valuation of the attributes shifted in the expected direction, with quality having a more positive ( $\beta_{\text {quality }}^{5}=$ 1.947 vs. $\left.\beta_{\text {quality }}^{25}=4.171\right)$ and travel distance having a more negative $\left(\beta_{\text {distance }}^{5}=-0.110 \mathrm{vs}\right.$. $\left.\beta_{\text {distance }}^{25}=-0.233\right)$ impact on consumers' choices as the number of treatments needed increases from 5 to 25 . Also, as before, option value is over-weighted $(\gamma=3.931, \mathrm{p}<.001)$. Here, in contrast to experiment 3 , the decision weights significantly differed from the objective probability of the future states (Decision weight $.10=.480, \mathrm{p}<.001$ ). As expected, and in line with theory, the future state with the low probability of materializing, received more weight than it should be based on its objective probability. Estimation results are reported in Table 8.

To evaluate the model's goodness of fit, we compared the loglikelihood and BIC of this model with the model without option value $(\gamma=0)$ and with the fully normative model (i.e., with $\gamma=1$ and the probabilities as decision weights). The results (see Table 9) show that the proposed behavioral model has the lowest loglikelihood and BIC, and therefore has the best model fit.

Table 8: Parameter Estimates Experiment 4

| Variable | Coef. | SE |
| :---: | :---: | :---: |
| $\boldsymbol{\beta}_{\text {quality }}^{5}$ | 1.947 *** | . 075 |
| s.d. $\boldsymbol{\beta}_{\text {quality }}^{\mathbf{5}}$ | 1.989 *** | . 083 |
| $\boldsymbol{\beta}_{\text {distance }}^{5}$ | $-0.110^{* * *}$ | . 007 |
| s.d. $\boldsymbol{\beta}_{\text {distance }}^{\mathbf{5}}$ | . $639^{* * *}$ | . 022 |
| $\boldsymbol{\beta}_{\text {quality }}^{25}$ | 4.171 *** | . 590 |
| s.d. $\boldsymbol{\beta}_{\text {quality }}^{25}$ | 4.276 *** | . 542 |
| $\beta_{\text {distance }}^{25}$ | -0.233 *** | . 034 |
| s.d. $\boldsymbol{\beta}_{\text {distance }}^{25}$ | 1.289 *** | . 021 |
| Decision weight $.10^{\S}$ | . 480 *** | . 024 |
| gamma ${ }^{\text {E }}$ | 3.931 *** | . 828 |
| Scale factor stage 1, 5 sessions ( $\mu_{1 \mathrm{a}}$ ) | Fixed to 1 |  |
| Scale factor stage 1, 25 sessions ( $\mu_{1 \mathrm{~b}}$ ) | . 813 *** | . 081 |
| Scale factor stage $2\left(\mu_{2}\right)$ | . 516 *** | . 076 |
| Scale factor stage $3\left(\mu_{3}\right)$ | . 351 *** | . 036 |

[^2]
# Table 9: Model Fit Comparison Experiment 4 

| Model | Loglikelihood | BIC |
| :--- | :---: | :---: |
| proposed behavioral model | -15279.14 | 30672.07 |
| $\gamma=0$ (no option value) | -15293.44 | 30707.16 |
| $\gamma=1$ (normative option value) | -15290.15 | 30700.58 |
| $\gamma=1$ and Decision weight $.10=.1$ (normative option <br> value and normative decision weight | -15293.63 | 30700.86 |

## Discussion

The results of experiment 4 underline the importance of allowing for decision weights when analyzing consumer option value if the probabilities of future states of the world are unequal. The results show that the estimated decision weights significantly differed from the objective $10 \%$ and $90 \%$ probabilities. The results of this experiment also replicate the earlier findings on the impact of option value in consumer product set choice and the importance of behavioral option value weighting.

## GENERAL DISCUSSION

Choosing a product now to use in the future is a common type of consumer purchase decision. Since the utility of alternatives in the future is uncertain, such forward buying decisions can be quite challenging. Firms can alleviate the potential negative impact of this uncertainty by introducing flexibility in consumers' choices. Offering consumers sets of products from which they can select the most suitable product in the future is an important way to offer such flexibility. To describe and predict consumer choices between such sets of products, this paper presents a model of consumer product set choice that is rooted in real option theory. We develop
a formal behavioral utility model for consumers' valuation of the real option value of product sets. The results of four experiments show that consumers do indeed account for the option value provided by a set when choosing between product sets for future product consumption. The results also support the two proposed behavioral effects of option value weighting and decision weights. In particular, they show that in the context of healthcare plan choices, consumers behaviorally overvalue option value (all four experiments) and attach greater decision weights to future states of the world occurring with small (vs. large) probabilities (experiment 4), but not when the future states are equally likely to occur (experiment 3 ).

## Theoretical implications

Our research contributes to previous literature on consumer option value in consumption in multiple ways. Although previous research in marketing has shown the importance of flexibility in product sets for future consumption (Bown, Read, and Summers 2003, Shin and Ariely 2004), in most models of consumers' product choice for future consumption to date, all products are consumed in the future (Dubé 2004; Guo 2006; Kim, Allenby, and Rossi 2002; Walsh 1995). We address the case where consumers can flexibly choose a single product from a set for consumption. This flexibility creates option value for the consumer, by alleviating the consequences of the uncertain outcomes in the future (Anderson et al. 2009; Sainam et al. 2010). By introducing option value in a normative model of consumer product set choice, we could empirically study and identify option value in decisions where consumers choose a product set now, and only choose a final product for consumption in the future. This analysis connects previous research streams on consumer product set choice and consumer option value.

We also contribute to the research on option value-based decision more generally. In particular, the results of the four experiments show that individuals not only take into account
option value but may also behaviorally overvalue its importance. The introduction of a behavioral option value parameter in our proposed model captures this effect and is an important extension of earlier normative work on option value in individual decision making (Belloni 2008; Ho, Tang and, Bell 1998; Kandel and Pearson 2002; Lee and Burris 2018; Stange 2012). The results in this paper show that consumers overvalue the importance of option value of a network and consequently are willing to pay a higher price to have greater flexibility. Moreover, as a second behavioral extension of normative models of decision making with option value, we incorporate individuals' subjective decision weights to replace the known probabilities of possible future states of the world when combining and weighting the corresponding outcomes of each state (Kahneman and Tversky 1979; Tversky and Wakker 1995). This behavioral aspect is important because option value, by definition, depends on the uncertainty of different future outcomes. Yet, in previous work on option value-based decision making such effects have not been incorporated (Capozza, Dennis, and Gordon 1991; Clapp, Bardos, and Wong 2012; De la Croix and Aude Pommeret 2021; Park, Sangkyun 2004). The results of the four experiments also provide empirical support for the proposed behavioral option value model.

Finally, we contribute methodologically to the marketing research literature by proposing a new three-stage choice experiment-based decision elicitation and modeling approach that can be used by researchers, marketing managers, and policymakers to estimate the proposed behavioral option value model and compare the added value of offering different levels of flexibility in sets for future product choices to consumers.

## Managerial implications

The results of the four experiments show that consumers attach utility to the option value of product sets for future consumption. These findings have important managerial implications
for companies offering sets of products for future consumption. Consumers can benefit from postponing choosing the products for consumption in many decision making procedures that involve uncertainty. The results of this research show that in the context of choosing a healthcare plan, a network with higher option value is valued greatly by consumers. Higher option value enables consumers to choose a more appropriate hospital and consequently, receiving better care in the future.

These findings have implications for other industries as well. For example, in education choices, offering students a greater range of elective courses that they can choose from after taking a core program (during which they can learn about their interests and aptitude) creates greater option value for students and can be highly valuable. As another example, offering cancer patients the flexibility to postpone their final treatment decision and wait for a next medical innovation can potentially be beneficial due to rapid technological advances. Similarly, with volatile climate conditions, and the fact that some leisure activities such as skiing and sailing require specific weather situations, the option value of postponing choosing the exact location and activities for a holiday destination is likely to be valued by consumers.

In terms of pricing, our findings imply that consumers are willing to pay more for a set that offers higher option value, and this has implications for firms' pricing of product sets for future consumption. This finding extends earlier research on how firms can benefit from consumers' uncertainty about future consumption by implementing pricing strategies such as option pricing, bundling, and advance selling (Sainam et al. 2010; Venkatesh and Mahajan 1993; Xie and Shugan 2001). The results of the studies show that, when choosing a health insurance provider, consumers are willing to pay more for a network offering more flexibility. Part of this willingness to pay originates from normative option value; however, the magnitude of $\gamma$ ), which
captures the over-valuing of option value, is such that it, further increases consumers' willingness to pay. Therefore, the results show that consumers are inclined to over-pay for flexibility compared to the normative option value. This finding has clear managerial implications.

To illustrate these managerial implications based on the results of experiment 3, we analyzed a case illustration of how adding an option to a set increases the overall utility by adding option value. Take as a baseline, two health insurance providers ( A and B ) who each have one clinic identical in their network with quality 8.5 , distance of 35 minutes, and intake fee of $\$ 40$ (clinics A1 and B1). Imagine that one health insurance provider considers adding a second clinic to its network with quality of 7 , distance of 5 minutes, and intake fee of $\$ 60$ (clinic B2). Based on the findings from our proposed model, adding the new clinic to the set would increase the utility of health insurance provider B by $8.6 \%$, while according to the normative model $(\gamma=1)$, the utility would be increased by only $0.17 \%$. To determine the added monetary value of the option value in terms of willingness to pay (Hess, Rose, and Hensher 2008), we calculated the monetary value of the more extensive set using the proposed model. For this purpose, we computed how much the intake fee of clinic A in the second network can be increased such that consumers equally prefer the networks with and without the second clinic. The result shows that the intake fee of the clinic B1 in B's network can be increased from $\$ 40$ to $\$ 53$. However, based on the normative model, the additional amount that could be charged would only be $\$ 0.50$ (i.e., $\$ 40$ to $\$ 40.50$ ). The difference between the initial intake fee and the new intake fee (i.e., $\$ 13$ ), is the increased premium that the health insurance provider would be able to charge for offering the more extensive network based on the behavioral model of option value.

## Limitations and future research

Our research also has a number of limitations that open up opportunities for future research. Firstly, we introduced a hypothetical scenario with a constrained setting on healthcare plan choices in the experiments. We examined a particular type of consumer decision making under uncertainty with two future states and three attributes of the alternatives. While we took great care in designing a stylized setting that resembles real-world conditions, future research can shed light on the role of option value in consumer decision making for healthcare plans by adding more attributes, different future health states, and different combinations of objective probability weighting of the future states. Future research could also study option value in other domains, such as investment decisions, holiday bookings, and education program selection. Combining choice experiment data with real market data in these sectors may also help further generalize conclusions regarding consumer decision making for future consumption.

In addition, we examined the beneficial role of flexibility in choosing a more compatible option at the time of consumption, which could be referred to as positive option value. Future research could examine other consumption cases where consumers do not necessarily experience greater flexibility as beneficial. For instance, when consumers are worried about self-control issues and want to avoid succumbing to their own future preferences, they may want to restrict (rather than expand) their options. For example, consumers may wish to save for retirement and block their future selves from ending a savings regime. In that case, lower option value can work as a commitment device and less flexibility can be seen as a positive feature by consumers.

A similar effect may occur, when consumers have to entrust a firm to select an option from the set for consumption. In such case, consumers might be willing to limit the option value of the set they choose from to minimize the odds of a less preferred option being selected for them by the firm. For example, if in the scenarios in our experiments, instead of being allowed to
freely choose any clinic from the network themselves, consumers would depend on the health insurance firm to assign them to a clinic of the insurer's choice, it is likely that, consumers would worry that they could be sent to a low-quality clinic. Therefore, in such a case, consumers may prefer lower flexibility and ignore the option value of the set if the insurer can choose a suboptimal clinic. However, we hope that, over time and on the basis of trust, consumers and firms can develop a better understanding of the added option value provided by flexibility in important choices such as healthcare insurance choices. Offering flexible sets of options at a price that balances consumer welfare and firms' long term financial sustainability needs can benefit society by overcoming the cost of future uncertainties.

## REFERENCES

Anderson, Eric T., Karsten Hansen, and Duncan Simester (2009), "The Option Value of Returns: Theory and Empirical Evidence," Marketing Science, 28(3), 405-423.

Bahaji, H. (2018), "Are Employee Stock Option Exercise Decisions Better Explained Through the Prospect Theory?." Annals of Operations Research, 262(2), 335-359.

Belk, Russell W. (1975), "Situational Variables and Consumer Behavior." Journal of Consumer Research 2(3), 157-164.

Belloni, Michele (2008), "The Option Value Model in the Retirement Literature: The Trade-Off between Computational Complexity and Predictive Validity." (Vol. 50). CEPS.

Bes, Romy E., Emile C. Curfs, Peter P. Groenewegen, and Judith D. De Jong (2017), "Health Plan Choice in the Netherlands: Restrictive Health Plans Preferred by Young and Healthy Individuals." Health Economics, Policy and Law, 12(3), 345-362.

Bhargava, Saurabh, George Loewenstein, and Justin Sydnor (2017), "Choose to Lose: Health Plan Choices from a Menu with Dominated Options," The Quarterly Journal of Economics, 132(3), 1319-1372.

Bleichrodt, Han, and Jose Luis Pinto (2000), "A Parameter-Free Elicitation of the Probability Weighting Function in Medical Decision Analysis." Management science, 46(11), 14851496.

Bown, Nicola J., Daniel Read, and Barbara Summers (2003), "The Lure of Choice." Journal of Behavioral Decision Making, 16(4), 297-308.

Capozza, Dennis R., and Gordon A. Sick (1991), "Valuing Long-Lerm Leases: The Option to Redevelop." The Journal of Real Estate Finance and Economics, 4(2), 209-223.

Clapp, John M., Katsiaryna Salavei Bardos, and Siu Kei Wong (2012), "Empirical Estimation of the Option Premium for Residential Redevelopment." Regional Science and Urban Economics, 42(1-2), 240-256.

Dafny, Leemore, Igal Hendel, and Nathan Wilson (2015) "Narrow Networks on the Health Insurance Exchanges: What Do They Look Like and How Do They Affect Pricing? A Case Study of Texas." American Economic Review, 105(5), 110-14.

De la Croix, David, and Aude Pommeret. (2021), "Childbearing Postponement, Its Option Value, and the Biological Clock." Journal of Economic Theory, 193, 105231.

DeLisle, R. Jared, Dean Diavatopoulos, Andy Fodor, and Kevin Krieger (2017), "Anchoring and Probability Weighting in Option Prices." Journal of Futures Markets, 37(6), 614-638.

Dellaert, Benedict GC, Bas Donkers, and Arthur Van Soest (2012), "Complexity Effects in Choice Experiment-Based Models." Journal of Marketing Research, 49(3), 424-434.

Donkers, Bas, Bertrand Melenberg, and Arthur Van Soest (2001), "Estimating Risk Attitudes Using Lotteries: A large sample approach." Journal of Risk and uncertainty, 22(2), 165195.

Dubé, Jean-Pierre (2004), "Multiple discreteness and product differentiation: Demand for carbonated soft drinks. " Marketing Science, 23(1), 66-81.

Ericson, Keith Marzilli, and Amanda Starc (2012), "Heuristics and Heterogeneity in Health Insurance Exchanges: Evidence from the Massachusetts Connector." American Economic Review, 102(3), 493-97.

Ericson, Keith Marzilli, and Amanda Starc (2015), "Measuring Consumer Valuation of Limited Provider Networks." American Economic Review, 105(5), 115-19.

Fischhoff, Baruch, and Stephen B. Broomell (2020), "Judgment and decision making." Annual review of psychology, 71, 331-355.

Gao, Song, Emma Frejinger, and Moshe Ben-Akiva (2010), "Adaptive Route Choices in Risky Traffic Networks: A prospect Theory Approach." Transportation research part C: emerging technologies, 18(5), 727-740.

Gollier, Christian, and Nicolas Treich (2003), "Decision-Making Under Scientific Uncertainty: The Economics of the Precautionary Principle." Journal of Risk and Uncertainty, 27(1), 77-103.

Gunther McGrath, Rita, and Atul Nerkar. "Real options reasoning and a new look at the R\&D investment strategies of pharmaceutical firms. "Strategic Management Journal, 25(1), 121.

Guo, Liang (2006), "Consumption Flexibility, Product Configuration, and Market Competition." Marketing Science, 25(2), 116-130.

Guo, Liang (2010), "Capturing Consumption Flexibility in Assortment Choice from Scanner Panel Data." Management Science, 56(10), 1815-1832.

Haenlein, Michael, Andreas M. Kaplan, and Detlef Schoder (2006), "Valuing the Real Option of Abandoning Unprofitable Customers When Calculating Customer Lifetime Value." Journal of Marketing, 70(3), 5-20.

Harris, Katherine, Jennifer Schultz, and Roger Feldman (2002), "Measuring Consumer Perceptions of Quality Differences among Competing Health Benefit Plans" Journal of Health Economics, 21(1), 1-17.

Heiman, Amir, David R. Just, Bruce P. McWilliams, and David Zilberman (2015), "A Prospect Theory Approach to Assessing Changes in Parameters of Insurance Contracts with an

Application to Money-Back Guarantees." Journal of Behavioral and Experimental Economics, 54, 105-117.

Hess, Stephane, John M. Rose, and David A. Hensher (2008), "Asymmetric Preference Formation in Willingness to Pay Estimates in Discrete Choice Models." Transportation Research Part E: Logistics and Transportation Review, 44(5), 847-863.

Ho, Teck-Hua, Christopher S. Tang, and David R. Bell (1998), "Rational Shopping Behavior and the Option Value of Variable Pricing." Management science, 44(12-part-2), S145-S160.

Huang, Chao, Mark Burris, and W. Douglass Shaw (2017), "Differences in Probability Weighting for Individual Travelers: A Managed Lane Choice Application." Transportation, 44(2), 375-393.

Kahn, Barbara E., and Donald R. Lehmann (1991), "Modeling Choice Among Assortments.", 274.
Kahneman, Daniel, and Amos Tversky (1979a), "On the Interpretation of Intuitive Probability: A Reply to Jonathan Cohen.".

Kahneman, Daniel and Amos Tversky (1979b), "Prospect theory: An analysis of Decision Under Risk." Econometrica, 47(2), 363-391.

Kandel, Eugene, and Neil D. Pearson (2002), "Option value, uncertainty, and the investment decision." Journal of Financial and Quantitative Analysis, 37(3), 341-374.

Kim, Jaehwan, Greg M. Allenby, and Peter E. Rossi (2002), "Modeling Consumer Demand for Variety." Marketing Science, 21(3), 229-250.

Kreps, David M. (1979), "A Representation Theorem for Preference for Flexibility." Econometrica: Journal of the Econometric Society, 565-577.

Lee, Sunghoon, and Mark W. Burris (2018), "Estimating the option value of managed lanes." Research in Transportation Economics, 70, 28-36.

Levett, Peter, Michael Page, Deon Nel, Leyland Pitt, Pierre Berthon, and Arthur Money (1999), "Towards an Application of Option Pricing Theory in the Valuation of Customer Relationships. " Journal of Strategic Marketing, 7(4), 275-284.

Liu, Yun, Qingxia Kong, and Esther W. de Bekker-Grob (2019), "Public preferences for health care facilities in rural China: a discrete choice experiment." Social Science \& Medicine 237:112396.

Louviere, Jordan J., David A. Hensher, and Joffre D. Swait (2000), "Stated choice methods: analysis and applications." Cambridge university press.

Luce, R. Duncan (1992), "Where Does Subjective Expected Utility Fail Descriptively?." Journal of risk and uncertainty, 5(1), 5-27.

Oppewal, Harmen, Jordan J. Louviere, and Harry JP Timmermans (1994). "Modeling hierarchical conjoint processes with integrated choice experiments." Journal of Marketing Research 31, no. 1:92-105.

Park, Sangkyun (2004), "Consumer Rationality and Credit Card Pricing: An Explanation Based on the Option Value of Credit Lines." Managerial and Decision Economics, 25(5), 243-254.

Payne, John W., John William Payne, James R. Bettman, and Eric J. Johnson (1993), "The adaptive decision maker." Cambridge university press.

Read, Daniel, and George Loewenstein (1995), "Diversification bias: Explaining the discrepancy in variety seeking between combined and separated choices." Journal of Experimental Psychology: Applied, 1(1), 34.

Revelt, David, and Kenneth Train (1998), "Mixed Logit with Repeated Choices: Households' Choices of Appliance Efficiency Level." Review of economics and statistics, 80(4), 647657.

Roberts, John H., Ujwal Kayande, and Stefan Stremersch (2014), "From Academic Research to Marketing Practice: Some Further Thoughts." International Journal of Research in Marketing, 31(2), 144-146.

Sainam, Preethika, Sridhar Balasubramanian, and Barry L. Bayus (2010), "Consumer Options: Theory and an Empirical Application to a Sports Market." Journal of Marketing Research, 47(3), 401-414.

Shin, Jiwoong, and Dan Ariely. (2004), "Keeping Doors Open: The Effect of Unavailability on Incentives to Keep Options Viable." Management science, 50(5), 575-586.

Simonson, Itamar. (1990), "The Effect of Purchase Quantity and Timing on Variety-Seeking Behavior." Journal of Marketing research, 27(2), 150-162.

Sonnier, Garrett, Andrew Ainslie, and Thomas Otter (2007), "Heterogeneity Distributions of Willingness-to-Pay in Choice Models." Quantitative Marketing and Economics, 5(3), 313331.

Stange, Kevin M. (2012), "An Empirical Investigation of the Option Value of College Enrollment." American Economic Journal: Applied Economics, 4(1), 49-84.

Swait, Joffre, and Wiktor Adamowicz (2001), "The Influence of Task Complexity on Consumer choice: A Latent Class Model of Decision Strategy Switching." Journal of Consumer Research, 28(1), 135-148.

Train, Kenneth, and Melvyn Weeks (2005), "Discrete Choice Models in Preference Space and Willingness-to-Pay Space." In Applications of simulation methods in environmental and resource economics (pp. 1-16). Springer, Dordrecht.

Trigeorgis, Lenos. (1993), "Real Options and Interactions with Financial FLexibility." Financial management, 202-224.

Tversky, Amos, and Peter Wakker (1995), "Risk Attitudes and Decision Weights." Econometrica: Journal of the Econometric Society, 1255-1280.

Venkatesh, Ramaswamy, and Vijay Mahajaim (1993), "A Probabilistic Approach to Pricing a Bundle of Products or Services." Journal of Marketing Research, 30(4), 494-508.

Walsh, John W. (1995), "Flexibility in Consumer Purchasing for Uncertain Future Tastes." Marketing Science, 14(2), 148-165.

Wedig, Gerard J. (2013), "The Value of Consumer Choice and the Decline in Hmo Enrollments." Economic Inquiry, 51(1), 1066-1086.

Xie, Jinhong, and Steven M. Shugan (2001), "Electronic Tickets, Smart Cards, and Online Prepayments: When and How to Advance Sell." Marketing Science, 20(3), 219-243.

Zhu, Jingrong, Jinlin Li, Zengbo Zhang, Hao Li, and Lingfei Cai (2019), "Exploring determinants of health provider choice and heterogeneity in preference among outpatients in Beijing: A labelled discrete choice experiment." BMJ open, 9(4), e023363.


[^0]:    ${ }^{1}$ Utility components in the equations are individual specific (unless indicated otherwise). For clarity of notation, the subscript $i$ is omitted.

[^1]:    ${ }^{2}$ The standard deviations for quality and distance in all experiments result from the Cholesky decomposition of the covariance matrix to allow for correlation between the quality and distance parameters. The standard error for these standard deviations are calculated using resampling of the normal distribution.

[^2]:    ${ }^{\S}$ Tested against 11
    ${ }^{\text {E }}$ Tested against 1
    a Random coefficients covariances not included in the table for clarity.
    Significance: ${ }^{* * *: ~<.001, ~ * *: ~<.01, ~ *: ~<. ~} 05$

