informs
http://pubsonline.informs.org/journal/mnsc

MANAGEMENT SCIENCE
Vol. 68, No. 8, August 2022, pp. 6075–6099
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Turning on Dimensional Prominence in Decision Making: Experiments and a Model

Ayala Arad,[a] Amnon Maltz[b]

[a] Coller School of Management, Tel Aviv University, Tel Aviv 69978, Israel; [b] Department of Economics, University of Haifa, Haifa 3498838, Israel

Contact: aradayal@tauex.tau.ac.il, https://orcid.org/0000-0002-8562-3447 (AA); amaltz@econ.haifa.ac.il, https://orcid.org/0000-0003-3488-8223 (AM)

Received: January 9, 2020
Revised: December 17, 2020; April 30, 2021
Accepted: June 22, 2021
Published Online in Articles in Advance: January 21, 2022

https://doi.org/10.1287/mnsc.2021.4205

Abstract. Could introducing a tiny interest rate on positive balances of checking accounts affect investment decisions? We suggest, counterintuitively, that it might decrease allocations to checking accounts and increase riskless investments with higher returns. This violation of monotonicity is a potential outcome of a novel behavioral phenomenon that we formalize and investigate experimentally. It posits that even a small interest rate highlights or *turns on* the safe gains dimension, bumping up its decision weight while shrouding other considerations, such as liquidity. Consequently, choices may shift from the most liquid option, the checking account, to safe investments with superior returns. Our exploration of this phenomenon covers three different choice environments: investment decisions, social preferences, and choice under uncertainty.

History: Accepted by Yan Chen, behavioral economics and decision analysis.
Funding: This work was supported by The Henry Crown Institute of Business Research in Israel, The Solomon Lew Center for Consumer Behavior, The Coller Foundation.
Supplemental Material: Data are available at https://doi.org/10.1287/mnsc.2021.4205.

Keywords: attention • dimensions • experiment • salience • social preferences

1. Introduction

Imagine that as the new year approaches, your employer tells you that you are about to receive a bonus of $2,000. The bonus will be transferred to one of three options, according to your choice: your checking account that generates no interest, a savings plan that yields 4% yearly interest for sure, or a stock that has a 50–50 chance to go up (and earn 14%) or down (and lose 5%). Which option would you choose?

Now, suppose that you are given similar options, but your checking account generates a small interest rate, say 2%. Would you choose differently? And what if it yields 0.1%? We suggest that this seemingly minor change of the choice set may have large and counterintuitive effects on choice through the following psychological channel: When the checking account carries no interest, it is mostly evaluated as a liquid tool. A person who highly values liquidity is likely to choose it. When a positive interest rate is introduced, the nature of the checking account changes. Specifically, it now draws attention to another dimension: safe gains. As a result, this dimension becomes more prominent and receives larger weight at the expense of liquidity, which is now shrouded. As the savings plan performs best on the safe gains dimension, the same person may now prefer the savings plan. Thus, our procedure suggests a nonmonotonic response to the introduction of the interest rate on the checking account: it is less likely to be chosen while the savings plan's likelihood of being chosen increases.

In this paper, we introduce, formally and experimentally, a decision process based on the idea that dimensions of a given option may be *turned on* in the decision maker's mind, that is, grab the decision maker's attention, or *turned off,* depending on the dimensions' values and the way they are framed. If dimension k is turned on in more alternatives than dimension j, then dimension k is more prominent and receives a larger weight than j when evaluating the alternatives in the choice set. In the preceding example, the checking account had the safe gains dimension turned off when it carried no interest, and it was turned on when a positive interest was introduced. As a result, the safe gains dimension received a larger weight in the latter scenario.

Our contribution to the literature is twofold: First, we formally add the role of turned-on dimensions into a choice model that is based on the literature on salience and focusing (Kőszegi and Szeidl 2012, Bordalo et al. 2013). As in that literature, we assume that subjective decision weights depend on context. However, our procedure places a spotlight on turned-on dimensions as the underlying feature that affects decision weights, whereas in the preceding models, weights are determined by the variance of the dimensions' values. As we elaborate, the existing models are unable to accommodate our findings, which stem from the discontinuous nature of turning-on dimensions. At the same time, we do not attempt to replace these models as they capture important determinants of salience in choice. Rather, we suggest that the two approaches may be combined into an augmented model with more predictive power. Our second contribution is in providing experimental evidence from three different contexts for the role of turned-on dimensions in determining decision makers' relative weighting.

The model we introduce, dubbed the turning-on dimensions (ToD) model, formalizes the intuition behind our checking account example. It consists of three building blocks: (i) alternatives have some dimensions turned on and others turned off, (ii) dimensional decision weights are determined by the number of instances in which turned-on dimensions appear in the choice set, and (iii) decision weights are applied uniformly to all available alternatives as in Kőszegi and Szeidl (2012). The essence of the model lies in the first of these blocks, that is, in the notion that dimensions may be turned on or off.

What determines whether a dimension is turned on in an alternative? According to our approach the answer lies in the value that the alternative has in that dimension and, specifically, whether it lies in that dimension's attractive facet. For desirable dimensions, the attractive facet is the range of values that are strictly greater than zero. Thus, the dimension of safe gains is turned on in the checking account when the account carries an interest rate that is larger than zero, and it is turned off otherwise. On the other hand, undesirable dimensions' attractive facet is highlighted when their value equals zero. For example, imagine that you are searching for an apartment. If one of the apartments has a laundromat in the basement, it emphasizes the proximity between the apartment and the nearest laundry service because it is literally right there, that is, zero meters away. On the other hand, if all apartments you are considering have the nearest laundromat in the neighborhood but not in the building, then the distance between each apartment and the nearest laundry service is less likely to receive much attention. In the next section, we formally define the notion of turned-on dimensions for desirable and undesirable dimensions.

The model's second building block describes the formation of decision weights. The only requirement we impose with respect to this stage is that dimensional weights are monotone with respect to the prevalence of turned-on dimensions. In other words, if dimension i is turned on in more alternatives than dimension j, the decision weight of dimension i is larger. Finally, in the last stage of the model, the decision maker settles the choice problem by applying the decision weights to all available alternatives. This three-step procedure predicts that even small changes to some alternative's dimensional value can generate preference reversals among unchanged alternatives, very much as in the literature on context effects. In this literature, the addition of, say, a dominated or extreme alternative to the choice set affects the relative subjective ranking of other alternatives in the set (Tversky 1972, Huber et al. 1982, Simonson 1989, Tversky and Simonson 1993). We elaborate on the relation of our findings to these types of context effects in Section 2.

Through the lens of turned-on dimensions and their effect on decision weights, we examine results from three studies that were conducted in three different choice contexts. We show how the psychological procedure underlying the ToD model is able to explain the findings in each context and examine when other leading theories in the existing literature fall short of doing so.

Our first study follows the motivating investment example. It shows that turning on dimensions may be "strong enough" to cause violations of the basic premise of monotonicity in money. Participants are asked to imagine that they are about to receive a bonus from their employer and are requested to choose whether the money is to be deposited into their checking account, a savings plan that generates 4% annual interest, or a stock that has a probability of 0.5 of going up (and earning 14%) or down (and losing 5%). In the first treatment, the checking account pays no interest, and in the second, it generates an annual interest of 2%. All other details are unchanged across treatments.

We find that a smaller percentage of participants choose the checking account when it pays a 2% interest rate. This drop in choice-share translates into a larger share of participants choosing the savings plan but does not affect the share of participants who choose the stock. The interest-generating checking account is chosen less frequently, we claim, because it has the safe gains dimension turned on. As a result, the safe gains dimension receives a larger overall weight in the consideration of all three options, and the savings plan, which performs best along this dimension, becomes more attractive. Liquidity, on the other hand, is shrouded and, as a result, receives lower weight in the decision problem. This underlying psychological mechanism is further supported by an analysis of participants' ex post explanations alongside findings from an experiment in which we directly elicit prominent dimensions in this context.

The second study is designed to illustrate the effect of turning on an undesirable dimension in an incentivized experiment. Participants are asked to rank three monetary allocations that will be paid out to them and to another participant. Using a between-subject design, we examine rankings in two treatments, named *equal* and *unequal*, that differ in the first allocation: in the equal treatment, it is a split that pays 100 ILS to both participants, and in the unequal treatment, it pays 100 ILS to the participant and 130 ILS to the other participant. The remaining allocations are identical across treatments and offer either a split of 100–140 or 100–160 (in both allocations, the smaller amount goes to the participant). In this context, we think of inequality as an undesirable dimension that is turned on in the presence of the all-equal split (i.e., a split with zero level of inequality).

We compare participants' relative rankings of the two unequal allocations that are identical across the two treatments and find significant differences. Specifically, rankings are more in line with inequality minimization in the equal compared with the unequal treatment. Looking into participants' ex post explanations, we find that egalitarian considerations are more pronounced and efficiency far less pronounced in the equal compared with the unequal treatment. Taken together, the findings show that the presence of the all-equal split turns on the inequality dimension and shifts preferences in the direction of less unequal allocations.

Our third study illustrates that weights can be shifted without actually changing the choice set, that is, by framing alone. In particular, we show, in the realm of uncertainty, that explicitly mentioning a desirable dimension of a lottery without changing its value turns that dimension on and increases its relative weight in the decision process.

The paper proceeds as follows: In Section 2, we review related experimental literature. Section 3 sets up the theoretical framework and outlines the main ingredients of the ToD model. Section 4 describes the experimental studies followed by the results. Section 5 examines other related theoretical approaches in light of our findings, and Section 6 concludes.

2. Related Literature

Our investment study relates to findings regarding violations of monotonicity. These are documented in intertemporal choice (Scholten and Read 2014, Cheng-Ming et al. 2017) and in the domain of uncertainty (Gneezy et al. 2006, Bateman et al. 2007) as well as in response to low incentives (Gneezy and Rey-Biel 2014). These studies argue that an objective improvement (such as a small payment in the future) may actually reduce the attractiveness of an alternative. Our work, on the other hand, focuses on how such improvements may shift dimensional weights and affect the evaluations of other unaltered options as well. For example, we argue that the apparent violation of monotonicity found in Study 1 is not because of the checking account being deemed worse when it generates a positive interest rate but rather because of the increase in the savings plan's evaluation. In fact, it is hard to argue that receiving a 2% annual interest from one's checking account is worse than not receiving any interest. This assessment is supported by another experiment reported in Study 1 according to which the checking account does not lose its popularity when there are no available options that outperform it along the turned-on dimension.

Our studies also share commonalities with experimental work on comparisons along different attributes.[1] For example, Slovic and MacPhillamy (1974) show that, in binary choices, attributes that are common to both alternatives are weighted more heavily than those that are unique. Building on this early work, Kivetz and Simonson (2000) show that this tendency may lead subjects to choose alternatives that have higher values of the common attributes. In their work, if, for some alternative, there is no information regarding the value of an attribute, then it is considered an uncommon attribute. In our studies, on the other hand, no information is missing, that is, all attributes are common to all alternatives. Nevertheless, our procedure suggests that, as an attribute is turned on in more alternatives, it receives higher weight in the decision process, which may be viewed as more comparisons along that attribute.

Comparability also allows individuals to find justifications or reasons for their choices that may be at the heart of many context-dependent behaviors. Consider, for example, the well-known decoy effect (Huber et al. 1982), which refers to the addition of a decoy option to a two-alternative set. When the decoy is dominated by one alternative but not by the other, preferences are found to shift in the direction of the dominating alternative. The experimental literature on this effect, also known as the attraction effect, is large and spans a variety of goods, services, and even perceptual decision tasks (Simonson 1989, Wedell, 1991, Ariely and Wallsten 1995, Dhar and Glazer 1996, Doyle et al. 1999, Scarpi 2008, Hedgcock et al. 2009, Trueblood et al. 2013).[2] One of the psychological explanations for this phenomenon is that individuals look for reasons to justify their choices (Shafir et al. 1993, Tversky and Simonson 1993).[3] Reason-based choice may be one of the underlying forces behind our findings as well. In fact, individuals may justify their choices based on turned-on dimensions as reflected by the higher weight that these dimensions receive in the decision procedure. However, despite the fact that our work and the decoy effect seem to share an underlying reason-based mechanism, our experiments and suggested procedure are significantly different than those in that literature.

First, our studies do not include a decoy option. In the investment scenario of Study 1, for example, the checking account is the most liquid option, which makes it desirable for quite a few participants. In Study 2, this point of difference is even more pronounced as the all-equal split of (100, 100) is actually the highest ranked alternative by many participants, let alone a decoy option. Second, in Study 1, the change we introduce to the choice set does not generate a shift of preferences between the two unaltered options (savings plan and stock) as the decoy effect would suggest. Instead, the slight improvement of the checking account shifts preferences away from it and in the direction of the savings plan while the stock's choice share remains the same. Finally, in Study 2, the options that differ between treatments, that is, (100, 100) and (100, 130), are either better than the two other options or worse than both of them for almost all of the participants (according to their own ranking). Thus, the preference shift generated by replacing one of them by the other is not due to an *asymmetric* dominance relation as in the decoy effect.

Another strand of literature that is related to our work deals with the special effect of zero. A number of studies show that an attribute with a value of zero may affect choice in a manner that goes way beyond standard cost–benefit analysis. For example, Shampanier et al. (2007) presented students with two chocolates: one of high quality and one of low quality. The price difference between the two chocolates was held constant across treatments (27 cents to 2 cents, 26 cents to 1 cent, or 25 cents to 0), but in the treatment in which the low-quality chocolate's price hits zero, the proportion of students who chose it peaked dramatically. The authors also provided evidence that the positive affect generated by a free offer is an important psychological factor that drives their results.[4] Palmeira (2010) examines the effect of zero with attributes other than price. He argues that, although a free offer, as in Shampanier et al. (2007), generates affect, a value of zero in other attributes does not. For other attributes, he claims, zero "takes the reference away" (Palmeira 2010, p. 18) and, hence, makes comparisons with other alternatives along that attribute more difficult. In a series of hypothetical experiments, he shows that increasing the value of an attribute of one alternative from zero to a small positive value may affect its choice share in a nonmonotonic fashion when another alternative outperforms it along that attribute.

Our work differs from these studies in a number of ways. First, our focus is not on the numerical zero value, but rather on what turns dimensions on or off in the mind of the decision maker. Second, the ToD model is not confined to one type of dimension or another. Specifically, it does not require identifying whether some dimension generates affect or not. Predictions may be generated based on whether the dimension is desirable or undesirable, a feature that is normally very easy to identify. Taking price as an example, our model allows formalizing the virtue of affect expressed in Shampanier et al. (2007): it is the extra weight placed on an undesirable dimension when it carries a value of zero. Lastly, in Study 2, we show that the channel of turned-on dimensions may reverse preferences over two options depending on the characteristics of a third option. Such an "indirect" effect on choice cannot be accommodated by the psychological procedures suggested in the zero-effect studies.[5]

Finally, Study 3 may be viewed through the channel of priming. Priming is an activation of mental processes through subtle situational cues (Bargh and Chartrand 2000). A large part of the priming literature focuses on prompting participants to think about a specific concept or recollect past experiences prior to some task and then measuring how participants' behavior is influenced.[6] Study 3 provides evidence for the activation of dimensional prominence through a different channel: making a dimension of some alternative explicit by framing, that is, turning it on, primes individuals to shift weight from other dimensions over to that dimension when settling their decision problem.

3. A Formal Derivation

We formalize the idea that turning on a dimension increases its weight in the evaluation of the choice set. Our model purposely ignores other factors that influence decision weights in order to focus on our suggested mechanism. Later, we sketch how one may add our channel of turned-on dimensions to those that have already been recognized in the literature on salience and focusing.

3.1. Dimensions

Every alternative has a number of characteristics that are relevant for choice. In most choice contexts, characteristics are not spelled out explicitly as part of the alternatives' description. In some specific contexts, as in many behavioral models or laboratory experiments, they are spelled out and given in the form of a list. In these circumstances, they are often referred to as attributes. There are also real-life examples in which some nonexhaustive set of relevant dimensions is mentioned explicitly but the rest are not.[7]

In our experiments, we do not use lists of attributes because our studies lie in the domain of choice contexts in which options are normally not described in this manner. We, therefore, allow participants to shape the dimensions that they deem relevant for choice. To avoid confusion with the existing literature, we use the term "dimensions" when referring to the characteristics that are relevant for choice from the decision maker's perspective. This allows us to refer to alternatives' characteristics when they are observable and when they are only partially observable, in a unified manner. Thus, if one is to apply our model to a specific context, the first step is to identify the relevant dimensions. The analyst may infer the relevant dimensions through introspection, prior knowledge, or more direct elicitation methods. In the context of Study 1, we illustrate in an experiment how one can directly elicit relevant dimensions: Participants are introduced with the same background and the same investment options as in the main experiment (checking account, savings plan, and stock) but are not asked to make a choice. Instead, we ask them to list the characteristics that come to mind when they examine each option. We also show that participants' ex post explanations of their choices may serve as a rough proxy for the list of relevant dimensions and make use of them in all of our studies.

3.2. The ToD Model

We follow Kőszegi and Szeidl (2012) (henceforth KS) and assume that our agent chooses from a finite set $\mathcal{C} \subseteq \mathbb{R}^K$ of K-dimensional objects and maximizes the following context-dependent weighted utility function:

$$\tilde{U}(c, \mathcal{C}) = \sum_{k=1}^{K} g_k(\mathcal{C}) \cdot u_k(c_k),$$

where $u_k(c_k)$ are the "consumption utilities" assigned to the different dimensions, as in KS, and $g_k(\mathcal{C})$ are the menu-dependent weights of each dimension. The difference between our ToD model and the one proposed by KS comes from the argument of the weighting functions $\{g_k\}_{k=1,\ldots,K}$ that measure the weight given to dimension k in the decision process. In KS, weights of the different dimensions correspond to their variance in the choice set: higher variance leads to a higher weight. Using the words of KS, "the decision maker focuses more on attributes in which her options generate a greater range of consumption utility" (Kőszegi and Szeidl 2012, p. 58). Our model suggests a different determinant for these weights, one that we believe is natural and also sheds light on the findings to follow. To formally express these weights, we first need to explain what it means for a dimension to be turned on in an alternative. We provide two definitions, the first for desirable dimensions and the second for undesirable ones.

Definition 1 (Turned-on Desirable Dimensions). We say that a desirable dimension k is turned on in alternative c if $c_k > 0$.

Definition 2 (Turned-on Undesirable Dimensions). We say that an undesirable dimension k is turned on in alternative c if $c_k = 0$.

Applying the definitions depends on the context and relevant dimensions. In Study 1, we use the first of the two definitions as the manipulation applied across treatments is made to the interest rate of the checking account, which is clearly a desirable dimension. In the context of Study 2, we refer to the second definition because we tweak the undesirable dimension of inequality. Specifically, replacing (100, 130) with the all-equal (100, 100) split pushes its inequality level to zero, the level for which it is turned on. Separating the definitions into desirable and undesirable dimensions is a convenient way to express our idea formally, but it is actually not necessary. We could say that every dimension, desirable or undesirable, has a range of "attractive values" that correspond to its attractive facet. This range is $(0, \infty)$ for desirable dimensions, and it is $\{0\}$ for undesirable dimensions. If we use this terminology, then any dimension $i \in \{1, \ldots, K\}$ is turned on in an alternative x if x_i belongs to the range of attractive values of dimension i.

Study 3 suggests that a dimension may be turned on in an alternative by simply describing it differently. However, a formal derivation of turning-on dimensions by framing requires reference to language rather than to numerical values, which is beyond the scope of this paper. In other words, in our model, framing is assumed to be held fixed while only numerical values may change. Nonetheless, in a less formal manner, in Study 3, we treat a dimension as turned on in an alternative if it is explicitly mentioned in that alternative's description and turned off otherwise.

Next, we define, for every alternative c, the K-vector of turned-on dimensions c^{ToD} by

$$c_i^{ToD} = \begin{cases} 1, & \text{if } i \text{ is turned-on in } c \\ 0, & \text{otherwise} \end{cases}$$

for every $i \in \{1, \ldots, K\}$. Following is our assumption on the weights.

Assumption 1 (ToD Weights). *The weights g_k^{ToD} are given by*

$$g_k^{ToD} = g\left(\left(\sum_{c \in \mathcal{C}} c_k^{ToD}\right) \Big/ \left(\sum_{j=1}^{K} \sum_{c \in \mathcal{C}} c_j^{ToD}\right)\right),$$

and the function $g : \mathbb{R} \to \mathbb{R}$ is strictly increasing.

For a given dimension, the ToD weights are calculated by dividing the number of alternatives in which that dimension is turned on by the total number of instances of turned-on dimensions in the choice set. In Study 1, for example, the safe-gain dimension receives a larger weight when the checking account's interest rate is raised from 0% to 2% (when it is 0%, this dimension is only turned on in the savings plan and, thus, carries smaller weight). We do not impose any additional structure on g although it is natural to concentrate on cases in which $g'' < 0$ and $g(0) = 0$. The first restriction implies that turning on a dimension in one more alternative has diminishing effects on the weight of that dimension as the number of alternatives in which that dimension is turned on grows. The second simply states that, when a dimension is turned off in the entire set, it does not receive any weight in the decision process. We emphasize that these weights are merely one technical formulation that allows us to capture the conceptual idea that turned-on dimensions affect decision weights. Our goal in this section is not to provide the best quantitative fit for actual decision weights.[8] Rather, we offer a simple formulation that captures the directional change behind our suggested mechanism.

The ToD model allows for discontinuities of weights with respect to small changes in the values of dimensions of alternatives. For example, a 0% checking account has the safe-gain dimension turned off, but a 0.1% interest rate turns it on and increases that dimension's weight. This "jump" in weight is the same whenever the interest rate increases to some positive number, no matter how small. This differs from the continuous nature of weights implied by KS. In their model, if the function g is continuous, small changes to a dimension's value lead to small changes in its relative weight.

As is common in the development of theoretical models, our approach is not meant to replace the insights of the existing focusing and salience models, both of which capture important features of human behavior.[9] Moreover, it is quite obvious that the channel of turned-on dimensions is not the only one to affect dimensional weights in a given context. In fact, we believe one has to take into account our insights alongside those from previous work. For example, one can think of a model with decision weights that are determined by both the variance of dimensional values and the number of turned-on dimensions. Such an extension allows for continuous effects of dimensional values based on the variance of each dimension as in KS without compromising the discontinuities around the "turning-on" point of these dimensions. In situations in which all dimensions are turned on, the variance component dominates. However, when some of the dimensions are turned on and some are turned off, the component reflecting the ToD procedure is likely to kick in and influence the decision weights.

3.3. Remarks

- One can make a simplifying assumption by taking g to be the identity function. In this case, the overall weights sum up to one. Thus, an increase in the weight of a specific dimension reduces the weight given to others. Making this assumption highlights the importance of relative weights, that is, turning on a dimension increases that dimension's prominence while masking other dimensions at the same time.
- Our model generalizes the standard linear utility model, and it reduces to it by imposing $g = 1$. KS refer to this benchmark case as *consumption utility.*
- As in KS, our weights apply to the evaluation of all alternatives in the set. In this sense, both models differ from the one proposed by Bordalo et al. (2013) in which dimensions' salience and, hence, their weights, may differ across alternatives.

4. Experimental Studies

We illustrate the effect of turned-on dimensions in a wide range of choice contexts. Study 1 deals with investment decisions in which we turn on a positive dimension (safe gains). In Study 2, we turn on a negative dimension (inequality) in the context of social preferences. Finally, Study 3 deals with choice under uncertainty and shows how dimensions may be turned on through framing.

4.1. Study 1: Enhancing the Checking Account in Investment Decisions

Our first study is based on the investment choice scenario described in the introduction. The study consists of four experiments and examines the effect of adding an interest rate to the checking account on individuals' investment decisions.

4.1.1. Experimental Design. Participants in the main experiment of this study were 201 registered panelists who regularly complete online questionnaires and constitute a representative sample of the Israeli adult population. Their age range was 18–65, and roughly 50% were female. A link to the questionnaire was sent out, and those who completed it received 5 ILS (roughly $1.5 at the time of the experiment). It took participants, on average, five minutes to complete two questions, each followed by a free text explanation of their answers. Participants were asked to imagine they are employed in a firm and about to receive a new year's bonus of 10,000 ILS (roughly $3,000). They were then asked to choose one of the following options to which the employer would transfer the money:

- Their checking account.
- A savings plan that generates 4% yearly interest.
- A stock that has a 50–50 chance of going up (earning 14%) or down (losing 5%).

Participants were randomly assigned to one of two treatments. In the 2-*checking* treatment, the checking account paid a 2% yearly interest rate. In the 0-*checking* treatment, the checking account earned no interest.

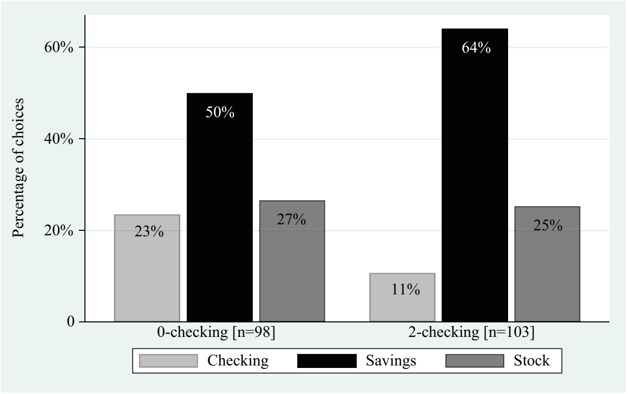
All three options were explained in detail, including withdrawal options and renewal terms, and in the most realistic fashion. The savings plan allowed weekly withdrawals and the stock could be sold anytime (online or by phone). It was also stated that they may withdraw any part of the bonus before the end of the year and reap the relative profits.[10] We also ran an almost identical experiment (with minor wording changes) with a checking account that had only a tiny yearly interest of 0.1% compared with a 0% checking account ($n = 207$).

In another experiment, which is a 2-option variation of the main experiment, we examined the same question given the same investment scenario but this time without the savings plan. We introduced 214 participants (with similar demographic characteristics to those in the main experiment) with the same backstory and asked them to choose between transferring the amount into their checking account (with no interest rate or a 2% interest rate depending on the treatment) or the stock. The purpose of this experiment was to examine whether introducing the interest rate on the checking account in the previous experiment may have actually reduced its attractiveness through some unexpected channel. For example, in Israel, most checking accounts do not generate interest, and some individuals may have grown accustomed to it. Having said that, we do not expect the added interest rate to make the checking account worse per se. The ToD procedure suggests that the added interest rate shifts choices only to alternatives that have a high interest rate, such as the savings plan. Therefore, in this experiment, in the absence of the savings plan, we expect to see the enhanced checking account chosen with a similar or higher percentage than the no-interest checking account.

4.1.2. Results. First, note that, although the checking account has a lower interest rate than the savings plan in both treatments, it has other merits (e.g., highest liquidity and most convenient withdrawal through the ATM) and is, therefore, not a dominated option. Indeed, a significant number of participants in both treatments choose this option, and their explanations show that they value precisely these merits. Some refer to the urgent need of liquid money (because of overdraft or other types of debt), and others mention the fact that they can invest the bonus later as they see fit because they can access it at any moment in time.

Standard consumer theory predicts a weakly higher share of participants choosing the enhanced checking account compared with the share of choices of the no-interest account. However, counterintuitively, the enhanced checking account is actually chosen less frequently. As shown in Figure 1, 23% of the participants choose the checking account with no interest, and

Figure 1. (Color online) Choice Percentages of Each Investment per Treatment in the Main Experiment of Study 1



only 11% do so when it generates a 2% interest ($p = 0.016$ according to a chi-squared test). This reduction translates into a significant increase in the share of participants who choose the savings plan (an increase of 15%, $p = 0.044$), and the percentage of participants who choose the stock shows no significant change ($p = 0.835$). In the experiment that used the tiny 0.1% interest rate, the percentages choosing the checking account, savings plan, and stock in the 0-*checking* treatment were 20%, 51%, and 28%, respectively, and in the treatment with the 0.1% interest rate, these percentages were 8%, 66%, and 26%. The percentage of choices of the checking account was significantly smaller, and the percentage of the savings plan significantly larger in the latter compared with the former ($p < 0.05$ for both comparisons).

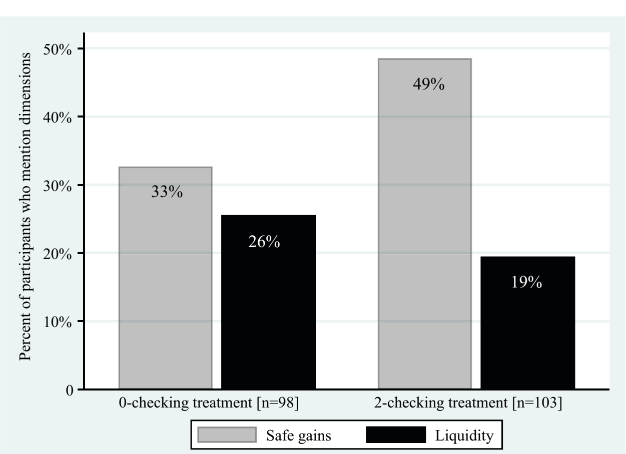
In the two-option variation experiment without the savings plan, we find that the added interest rate does not harm the checking account per se. In fact, in both treatments, more than half of the participants choose the checking account: 53.2% when it carries no interest and 52.4% when the 2% interest rate is added to it ($p = 0.946$ according to a chi-square test). In other words, the enhanced checking account (with a 2% interest rate) is not deemed worse than the one with no interest rate.

4.1.3. Explanation Analysis. In an attempt to gain insight into the psychological mechanism behind our participants' choices, we looked into participants' ex post explanations of their choices in the main experiment. We believe that these explanations shed light on the dimensional weights that participants held at the time of making a decision. For this purpose, we asked a research assistant (RA) to read the explanations and prepare a list of categories of relevant dimensions. We examined the list ourselves and approved it with no changes or adjustments. These categories were exhaustive and reflected the various dimensions that were mentioned by our participants. Then, three RAs, including the one who came up with the list of categories, independently classified explanations into these categories (one explanation could fit into a number of categories). After their initial independent classifications, we determined the final classification by majority rule. Classifications were made separately and independently by each RA. Unanimous classifications occurred for the vast majority of cases.[11]

Following the completion of the RAs' work, we realized that the most frequently mentioned dimensions were safe gains, liquidity, the possibility of high returns, and risk. In Figure 2, we see that participants refer to safe gains more often in the 2-*checking* treatment (49%) compared with the 0-*checking* treatment (33%) whereas, for liquidity, the pattern is reversed (19% compared with 26%, respectively). The former difference is significant according to a chi-square test (p = 0.022), but the latter is not (p = 0.3). The possibility of high returns and risk dimensions were mentioned with almost identical proportions in both treatments.[12]

The emerging pattern is well explained by the ToD procedure. When the checking account pays no interest, safe gains receives a lower weight in the evaluation of the entire choice set compared with its weight in the 2-*checking* treatment. As a result, liquidity's relative weight is larger, and because the checking account performs best along this dimension, it is chosen by roughly a quarter of the participants. When the checking account carries a positive interest rate, however, it has the dimension of safe gains turned on, which increases the relative weight attached to this dimension at the expense of liquidity (as well as the other two dimensions). With this weight shift, not much is left for the checking account to show for in this context. After all, along the safe-gains dimension, which is now more prominent, it is completely outmatched by the savings plan. Liquidity on the other hand, along which it performs better, is now shrouded and receives a smaller relative weight. As a consequence, it is chosen less frequently in this treatment. Of course, those who still highly value the liquidity dimension, because of, say, debt or an urgent need for money, may very well choose it even in this case.

Figure 2. (Color online) Dimensions Mentioned per Treatment in the Main Experiment of Study 1



In passing, we acknowledge the fact that ex post explanations are insufficient if one is interested in eliciting *all* relevant dimensions that were noticed by participants at the stage of contemplation of the choice set. Ex post explanations are naturally concentrated on dimensions of the chosen alternative rather than dimensions of the nonchosen ones. In addition, it is likely that these explanations involve rationalizations rather than first glance dimensional perceptions of the alternatives—the latter being our actual interest.

To partially accommodate these difficulties, we ran another experiment with the goal of directly eliciting the dimensions that come to mind when facing the investment options. In order to do so, we ran two treatments that are almost identical to those in our main experiment but with one important difference: in this experiment, participants were not asked to choose. Rather, after reading the same backstory as in the main experiment of Study 1, they were asked to write the characteristics that they deemed most prominent for each option. In Appendix A, we elaborate on this experiment, the analysis, and its results.

The main dimensions elicited in this more direct method are almost identical to those that emerged in the ex post explanations. The differences between the main dimensions that were mentioned across treatments are also similar to those in the ex post explanations. Given this similarity and keeping in mind the potential limitations raised earlier, in the following studies, we carry on with ex post explanation analysis as a proxy for our participants' perceptions of prominent dimensions.

4.1.4. Conclusion. Summing up, this study shows that adding a positive interest rate to the checking account may lead individuals to hold smaller balances in that account and, instead, allocate balances to other riskless assets. Standard theory cannot accommodate these findings because of the violation of monotonicity. Moreover, the two models of focusing and salience mentioned earlier (Kőszegi and Szeidl 2012, Bordalo et al. 2013) are also unable to explain this choice pattern. Notice that increasing the interest rate of the checking account from 0% to 2% reduces the variance of the interest rate in the choice set. According to Kőszegi and Szeidl (2012), decision makers should now focus less on this dimension, and it should receive a smaller decision weight. As a result, their model predicts that the savings plan should be chosen less frequently, and the other, more liquid options should gain popularity at its expense. According to Bordalo et al. (2013), increasing the checking account's interest rate would reduce the distance of the savings plan's interest rate from the average interest rate, and hence, this dimension becomes less salient in the evaluation of the savings plan. It should, therefore, be chosen (weakly) less. At the same time, the low interest rate of the checking account would be more pronounced when it is zero; hence, it should be chosen less in the 0-*checking* treatment (once again "pushing" choices in a direction that contradicts our findings). In Appendix B.1, we provide a numerical example illustrating that the ToD model accommodates these findings. Moreover, we show that the model generates forces that push in the direction of this behavioral pattern independently of the dimensional utility functions of safe gains and liquidity (as long as they are monotonic and continuous).

4.2. Study 2: Social Preferences in the Presence of an Equal Split

Study 1 dealt with turning on a desirable dimension by changing its value from zero to a positive level. We now show in two experiments how an undesirable dimension may be turned on when its value is shifted in the opposite direction, that is, from a positive level to zero. For this purpose, we chose the context of social preferences and explored how replacing an unequal allocation with an all-equal split of a pie turns on the undesirable dimension of inequality.

4.2.1. Experimental Design. Participants in the main experiment were 393 registered panelists that constitute a representative sample of the Israeli adult population. Their age range was 18–65, and roughly 50% were female. A link to the questionnaire, which included one question followed by a free text explanation, was sent out, and those who completed it, did so in about three minutes and received a participation fee of 3 ILS (roughly $0.9 at the time of the experiment). In addition, it was explained in the instructions that 5% of the participants would be randomly selected to receive additional payoffs according to their responses. Participants were randomly assigned to one of two treatments, named *unequal* and *equal*. In both treatments, they were presented with a situation in which the participant and another anonymous participant were chosen to receive payment. The participant was then asked to determine the exact payment for both the participant and the other participant. It was clearly stated that the identity of the other participant would not be disclosed.[13] In the *equal* treatment, one of the allocations was completely equal, and in the *unequal* treatment, all allocations were unequal. In another experiment that we call the *no-equality experiment*, a similar design was held in which both treatments comprise only unequal allocations.

Table 1, Panel A shows the different options that were available in each treatment in the main experiment. To control for order effects, each treatment had two opposing orders of the three options. Options *b* and *c* are unequal splits that are identical in both treatments, and the first option is different: an unequal split in one treatment (option *a*) and an equal split in the other (option *a*'). In each treatment, participants were asked to rank the options from their most to least preferred. In order to incentivize the full ranking, the instructions explained that, if the participant is drawn to receive payment, there is a 60% chance that the most preferred option will be implemented and a 40% chance that it will be the second ranked option.[14] Finally, participants were asked to provide a brief explanation for their ranking.

Our main interest is in the relative ranking of options *b* and *c* across treatments (top-ranked options across treatments are also reported). Ranking *b* above *c* reflects a stronger emphasis on reducing inequality, and the opposite ranking is in line with putting more weight on efficiency considerations. Notice that one does not sacrifice one's own payoff by increasing the other (anonymous) person's payoff. It is well documented that people care about both equity (Fehr and Schmidt 1999) and efficiency (Charness and Rabin 2002). In line with the latter, in our experiment, we expected most participants in both treatments to rank the outcome with the highest sum of payoffs, (100, 160), on top, which indeed was the case. Nonetheless, we examine the difference in rankings across treatments and its relation to the nature of the first option.

Table 1. Monetary Payments by Treatment in Study 2

Panel A		
Options	Unequal	Equal
a (*a*')	(100, 130)	(100, 100)
b	(100, 140)	(100, 140)
c	(100, 160)	(100, 160)
Panel B		
Options	Unequal130	Unequal110
a (*a*')	(100, 130)	(100, 110)
b	(100, 140)	(100, 140)
c	(100, 160)	(100, 160)

Notes. A pair (*x*, *y*) represents a payment of *x* ILS to the participant and *y* ILS to the other participant (at the time of the experiment, 100 ILS were roughly equal to $30). Panel A lists the payments of the main experiment, and Panel B lists the payments of the no-equality experiment.

The no-equality experiment includes two treatments, the options of which are summarized in Table 1, Panel B. Participants were 221 registered panelists with similar demographic characteristics to those in the main experiment. The first treatment is identical to the *unequal* treatment in the main experiment. Unlike that experiment, however, the second treatment also consists of unequal splits only. The only difference between treatments lies in the first unequal split. In the *unequal*130 treatment, the other participant receives 130 ILS, and in *unequal*110 the other participant receives 110 ILS (the participant choosing the allocation receives 100 ILS in all options). Replacing the (100, 130) allocation with (100, 110) rather than an all-equal split (as in the main experiment) allows us to emphasize the discontinuity of our decision procedure as we later elaborate.

4.2.2. Results. Starting with the main experiment, in the *unequal* treatment, only 18% rank *b* above *c*. In the *equal* treatment, this percentage rises to 32% ($p = 0.002$ according to a chi-squared test). In a logistic regression reported in Table 2, we control for the order of the alternatives and find a significant positive effect of the *equal* treatment on the probability of ranking *b* above *c*; the odds ratio equals 2.1 ($p = 0.002$). In other words, the probability to rank *b* above *c* divided by the probability to rank *c* above *b* doubles when the (100, 130) allocation is replaced with (100, 100).

In Table 3, we report the percentages of participants who rank each of the three options on top by treatment. This table reveals the shift of preferences from reflecting efficiency to inequality considerations across treatments in line with the preference reversal between options *b* and *c*. A significantly larger proportion of participants rank option *a*' on top in the *equal* treatment (38%) compared with those who rank *a* on top in the *unequal* treatment (14%). The difference in proportions is reversed looking at those who rank *c* on top: 82% in the *unequal* treatment compared with only 60% in the *equal* treatment (both differences are highly significant according to a chi-squared test: $p < 0.001$).[15]

Table 2. Main Experiment of Study 2: Logistic Regression

Variable	Coefficient
equal treatment	0.743***
	(0.241)
order	0.059
	(0.236)
cons	−1.542***
	(0.218)
N	393
R^2	0.0224

Note. The dependent variable equals one when *b* is ranked above *c* and zero otherwise. Standard errors in parentheses.

***$p < 0.01$.

Table 3. Top Ranked Options

Options	Unequal	Equal
a (*a*')	14% (28)	38% (76)
b	4% (7)	2% (4)
c	82% (159)	60% (119)

Note. Percentage of participants who rank each option on top (numbers of participants in parentheses).

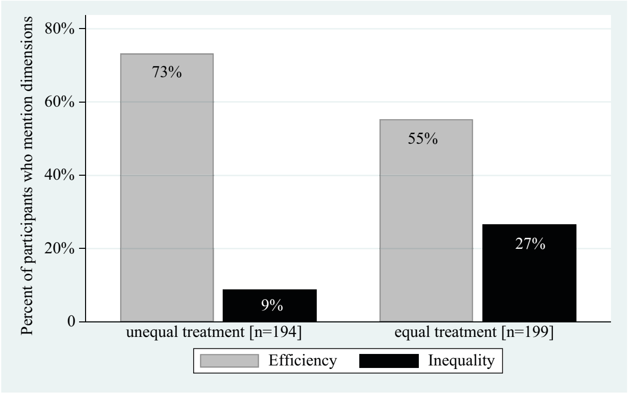
The results are completed when we add the findings from the no-equality experiment. No significant differences arise between the relative ranking of options *b* and *c* in this experiment: 24% rank *b* over *c* when the first option is (100, 130), and 17% do so when (100, 110) is the first option ($p = 0.182$). Thus, replacing (100, 130) with (100, 110) does not have the same impact on behavior as replacing it with (100, 100). If anything, there is a slight shift in the opposite direction to the one found in the main experiment.

4.2.3. Explanation Analysis. We gain insight into the underlying psychological procedure in the main experiment using participants' ex post explanations of their rankings as we did in Study 1 (and keeping in mind the limitations of these explanations). The same procedure described in Study 1 was held in this context using the good work of the three RAs. We concentrate on the two categories that were referred to the most: "inequality" and "efficiency." Explanations classified into the efficiency category included all arguments that support a larger payment to the other participant or a larger payment overall (recall that one's own payment remains unchanged). The inequality category contained all explanations that referred to equality, lack thereof, or simply inequality.

If, as we expect, the inequality dimension is weighted more heavily in the *equal* treatment, it should be mentioned there more often compared with the *unequal* treatment. Similarly, we expect the efficiency dimension to be more prominent in the *unequal* treatment compared with the *equal* treatment because it is not shrouded by the inequality dimension. Figure 3 summarizes our analysis of participants' explanations and shows that, indeed, inequality is mentioned more frequently in the *equal* treatment compared with the *unequal* treatment (27% compared with 9%), and the opposite pattern is found for efficiency (55% mention efficiency in treatment *equal* compared with 73% in treatment *unequal*). Both differences are highly significant according to a chi-square test ($p < 0.001$).

4.2.4. Conclusion. In the main experiment, we find that changing the value of the undesirable dimension of inequality to zero, by replacing (100, 130) with (100, 100), turns this dimension on and shifts weights

Figure 3. (Color online) Dimensions Mentioned per Treatment in the Main Experiment of Study 2



as predicted by the ToD procedure for any monotonic consumption utility functions. These findings cannot be explained by any type of stable preferences, that is, preferences that are context independent. Notice, however, that the focusing and salience models of Bordalo et al. (2013) and Kőszegi and Szeidl (2012) *are* able to predict them given specific parameters. This is because replacing (100, 130) with (100, 100) increases the variance of both efficiency and inequality in the choice set. However, looking at the main experiment alongside the no-equality experiment allows us to disentangle our suggested mechanism from the focusing and salience models and rule the latter out as potential candidates for explaining the results. To see this, note that, in the no-equality experiment, the directional variation in dimensions across treatments is the same as in the main experiment. Thus, the focusing and salience models predict a directional shift of the relative rankings that is similar to the one found in the main experiment, albeit perhaps slightly smaller in magnitude. The ToD model, however, predicts that, unlike the main experiment, there should be no significant difference in the relative rankings of options *b* and *c* in the no-equality experiment because the same dimensions are turned on in both treatments.

We find no significant shift in rankings (in fact, the insignificant shift that does arise is in the opposite direction from the one predicted by the focusing and salience models). Thus, the combined results point to the discontinuous effect of turned-on dimensions as the psychological mechanism underlying our findings rather than the effect of the change in variance. In Appendix B.2, we show that the ToD model predicts a preference shift that is in line with our findings from Study 2 regardless of the specific parameters of the consumption utility functions (as long as these functions are monotonic).

4.3. Study 3: The Framing of a Lottery in the Realm of Uncertainty

In our final study, which includes one experiment with four treatments, we demonstrate how framing may be used to turn on dimensions. We illustrate this in the realm of uncertainty by using different frames for the same lottery in the different treatments.

4.3.1. Experimental Design. Participants in this study consisted of 243 undergraduate students from various fields in Tel Aviv University, who are registered in the IDMlab of the Coller School of Management. Their age range was 18–35 (except for one older participant), and roughly 64% were female. The questionnaire consisted of one question followed by a free text explanation, and the average completion time was about five minutes. Participants were sent a link to the questionnaire and were asked to choose between two or three options, depending on the treatment. They were randomly assigned to one of four treatments named *certain*(2), *certain*(3), *lottery*(2), and *lottery*(3) and were instructed that 5% of them would be randomly selected to receive a prize according to their choice. Table 4 summarizes the options in our main treatments: *certain*(3) and *lottery*(3).[16]

Participants in *certain*(3) and *lottery*(3) face the same choice problems with one difference: in the former, the first option is framed as a certain amount (using the words "with certainty") plus a potential bonus, whereas in the latter, the first option is framed as a state-contingent lottery (probabilities and prizes) just as in the framing of option *b*. Therefore, the certainty dimension is more emphasized in the description of the first option in *certain*(3), and the probability of obtaining the high prize of 95 ILS is more emphasized in the description of the first option in *lottery*(3). Other lottery features, such as the probability of obtaining the low prize or the expected value are also more explicit in the state-contingent frame. According to the ToD procedure, this change of frame is expected to shift weights from the certain amount dimension in *certain*(3) to these lottery features in *lottery*(3). As a result, we expect option *b*, which does relatively well along

Table 4. Options by Treatment in Study 3

Options	Certain(3)	Lottery(3)
a (*a'*)	60 with certainty + 35 with probability 0.14	(0.86,60; 0.14,95)
b	(0.5,40; 0.5,95)	(0.5,40; 0.5,95)
c	Dow-J (30,115)	Dow-J (30,115)

Notes. A lottery with known probabilities is described by $(p,x;1-p,y)$, that is, probability p of winning x ILS and probability $1-p$ of winning y. A bet denoted by Dow-J (x, y) is a bet that pays x ILS if the Dow–Jones index goes up the following day and y if it goes down. (We use the term *lottery* to describe contingent claims in which probabilities are objective and known to the decision maker and *bet* for claims with unspecified probabilities).

some lottery features—has a high known probability of delivering the large 95 prize and a high expected value—to receive a larger share of choices in *lottery*(3) compared with *certain*(3). The first option, on the other hand, is expected to have a lower choice share in *lottery*(3) compared with *certain*(3) because the certainty dimension is shrouded in the former.

To further investigate the ToD procedure in this context, we turn to the *lottery*(2) and *certain*(2) treatments. These are the same as *lottery*(3) and *certain*(3), respectively, except that option *b* (the 50–50 lottery) is absent. Hence, the difference in the weighting of dimensions should be in the same direction as in the main treatments, but in the absence of *b*, we do not expect the share of the first option to decrease. The reason is that the lottery features, which have been turned on in option *a*', are not shared by *c*, the other alternative in the set. Thus, no other option, except for *a*', is expected to gain from the larger weight given to these features in contrast to our main treatments in which we expect option *b* to do exactly that—gain from the larger weight placed on the lottery features because of the framing of *a*'.

Note that option *c* may benefit from the shift in weights along some other unforeseen channel, and the combination of the four treatments in this study allows examining this possibility. This is done in a similar vein to the exploration of adding the interest rate to the checking account in the absence of the savings plan (the second experiment of Study 1). Our complete hypothesis, based on the ToD procedure, states that changing the certain framing to the lottery framing will lead to a more substantial decrease in the first option's choice share when option *b* is present than when it is absent.

4.3.2. Results. A logistic model is estimated to test if the treatment has an effect on the likelihood of the first lottery (presented as *a* or *a*') to be chosen. The probability that the first lottery is chosen is modeled by $\sigma(\tilde{Y})$, where σ is the cumulative distribution function of the standard logistic distribution and $\tilde{Y}$ is specified as follows:

$$\tilde{Y}_i = \beta_1 lottery(2)_i + \beta_2 certain(3)_i + \beta_3 lottery(3)_i + \epsilon_i,$$

where $lottery(j)_i, j = 2, 3$ is a dummy variable that equals one if participant *i* was assigned to treatment lottery(*j*), $certain(3)_i$ is a dummy variable that equals one if participant *i* was assigned to treatment *certain*(3), and ϵ is an error term distributed by the standard logistic distribution. The benchmark treatment is taken to be *certain*(2) in which participants choose between option *a*, framed as a certain amount of money plus a possible bonus, and the Dow–Jones bet. Coefficient β_1 measures the net effect of framing the first lottery as *a*', and β_2 measures the effect of adding option *b* to the choice set without changing the frame, that is, moving from a doubleton set (without *b*) to a triplet (including *b*). β_3 is the coefficient of the interaction variable, which equals one when the first lottery is framed as *a*' and option *b* is present. Our main interest lies in the odds ratio implied by this coefficient, that is, the effect of changing the frame *and* having *b* in the set on top of the two separate main effects. Formally, our main hypothesis is that the odds ratio implied by β_3 is smaller than one, that is, the interaction variable has a negative effect on the probability of choosing the first lottery.

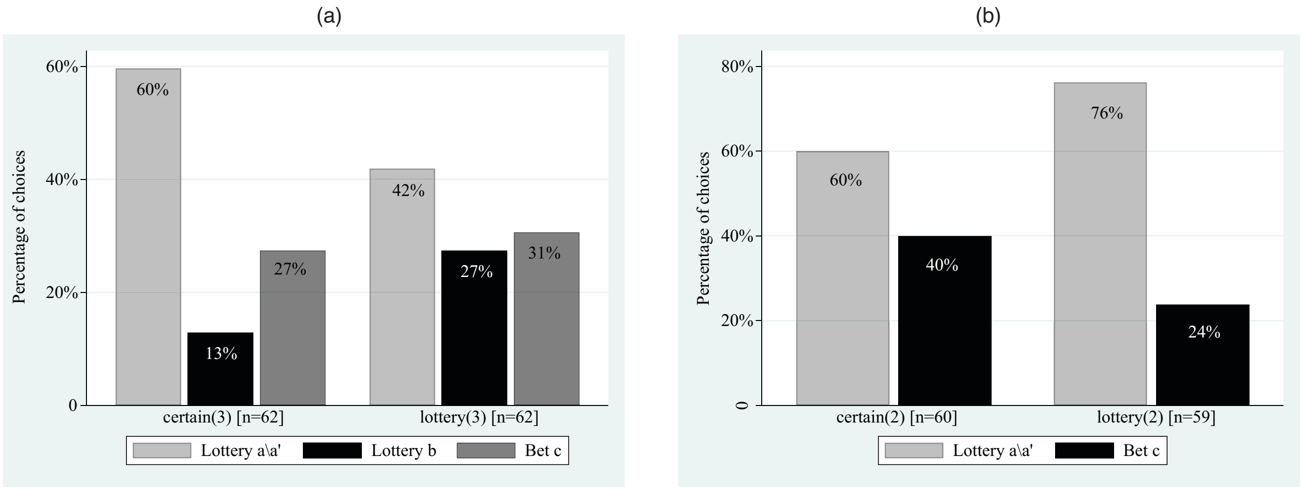
Our full results are summarized in Table 5. Our hypothesis is confirmed by the data as the odds ratio of the interaction variable equals 0.23 (p = 0.007). In addition, the coefficient of adding option *b* is not significantly different from zero, and the effect of only changing the frame is actually almost significantly positive (p = 0.059). In other words, adding option *b* without changing the frame or changing the frame without adding option *b* does not negatively impact the frequency of choosing the first option. It is only the combination of the two that increases the choice frequency of *b* at the expense of *a*'. Figure 4 gives another perspective of the same effect: in panel (a), we can see that 60% of the participants choose the first option in *certain*(3), and only 42% do so in *lottery*(3). This significant reduction (p = 0.048 according to a chi-squared test) translates into an increase in the choice share of lottery *b* (an increase of 14%, p = 0.044) but does not significantly change the percentage of participants who choose to bet on the Dow–Jones (p = 0.692). This increase in the choice share of *b* arises despite the fact that *a*' is more popular than *a* when compared with *c* alone as shown in panel (b) (76% choose *a*' in *lottery*(2) compared with 60% that choose *a* in *certain*(2)).

Table 5. Study 3: Results of a Logistic Regression

Variable	Coefficient
lottery(2)	0.762*
	(0.404)
certain(3)	−0.013
	(0.369)
lottery(3)	−1.48***
	(0.544)
cons	0.405
	(0.263)
N	243
R^2	0.0461

Notes. The dependent variable equals one when the first option is chosen and zero otherwise. Standard errors in parentheses.
***$p < 0.01$; *$p < 0.1$.

Figure 4. (Color online) Choice Percentages of Each Option in Study 3

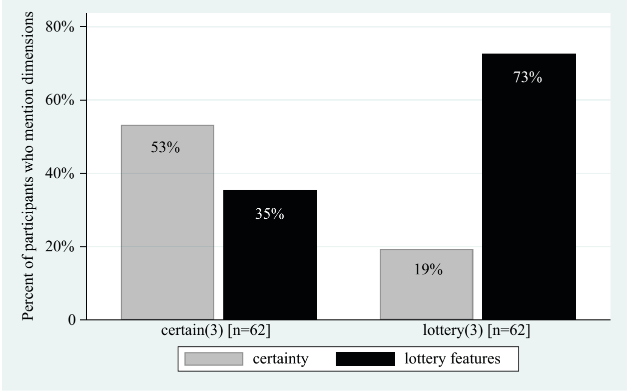


Notes. Both panels compare the effect of framing on the choice distributions. Panel (a) does so for the choices from triplets (*certain*(3) and *lottery*(3)), and panel (b) compares the choices from binary sets (*certain*(2) and *lottery*(2)).

4.3.3. Explanation Analysis. Further support is given in Figure 5 that reports participants' ex post explanations in a way that is analogous to our examination of explanations in the previous studies. We focus again on the two most common dimensions: *certainty* (i.e., a certain amount or a sure gain) and *lottery features*. Lottery features are explanations that refer to expected values and considerations of known probabilities (as opposed to unknown probabilities) to obtain a maximal or a minimal prize. The figure shows that participants in treatment *certain*(3) mention certainty far more frequently than participants in treatment *lottery*(3) (53% compared with 19%, $p < 0.001$, chi square test), and the prevalence of lottery features in the explanations is reversed (35% compared with 73%, $p < 0.001$).

4.3.4. Conclusion. This study demonstrates the role of framing in turning-on dimensions: explicitly mentioning a dimension brings it to the mind of the decision maker and shifts weights in its favor. An illustration of how the ToD procedure accommodates our findings from the four treatments of this study is given in Appendix B.3. Although our model does not capture turning-on dimensions through framing, for the purpose of this exercise, we assume that dimensions are turned on when they are explicitly mentioned in the description of the alternative. Note that the focusing and salience models are not set up to deal with framing effects and, hence, cannot account for the findings from this study.[17]

Figure 5. (Color online) Dimensions Mentioned in Treatments *Certain*(3) and *Lottery*(3)



5. Predictions of Other Models

In this section, we briefly discuss our model, alongside other approaches, in light of the behavioral patterns that arise in our studies. The closest models are those of Kőszegi and Szeidl (2012) and Bordalo et al. (2013). We draw on the idea, which is common to both models, that some characteristics stand out more than others and receive larger weight in the assessment of goods. The main difference between our model and theirs lies in how weights of different dimensions are determined. In these models, a dimension with a wider range becomes more prominent and receives a larger weight. In the ToD model, a dimension's prominence is determined by the number of alternatives in which it is turned on. In this sense, our model is more "discontinuous" than the focusing and salience models. For example, slightly decreasing the level of some dimension of one alternative but keeping that level positive is likely to have some effect on its prominence according to these models but not according to ToD. By contrast, a tiny dip in the level of some dimension from $\epsilon > 0$ to zero is likely to generate a larger effect on relative prominence in our model than in theirs. As shown, these models cannot explain our experimental findings, but the ToD model is able to do so.

An approach closely related to focusing and salience, which is interesting to examine in light of our findings, is that of relative thinking. Bushong et al. (2021) derive a model that formally resembles Kőszegi and Szeidl (2012) but assumes that the decision maker places less weight (rather than more weight) on dimensions with larger variance of consumption utility.[18] Using the authors' example, the model predicts that the difference between losing 12$ and losing 13$ looms larger when the range of possible losses is 13$ compared with when the loss range is 25$. Although relative thinking, as focusing and salience, is an important phenomenon of human behavior, it is unable to accommodate our findings. As in the case of focusing, we believe that the reason lies in the discontinuous nature of our findings, which is reflected by the ToD procedure but is not incorporated by the relative thinking model. For example, consider Study 1. One of our experiments compared choices across the same sets as in the main experiment, in which one had a checking account with a tiny interest rate of 0.1% and the other included a checking account with no interest rate. A similar distribution of choices arises when the checking account carries a 0.1% interest rate or 2% and both distributions are different than the one that arises when the checking account has no interest rate. The ToD model suggests that, as long as the interest rate is strictly greater than zero, the safe-gains dimension is turned on in the checking account, generating the same dimensional weights across the two experimental versions that are different than those in the corresponding 0-*checking* treatments. According to the relative thinking theory of Bushong et al. (2021), we would expect similar distributions of choices when the checking account carries no interest rate and when it generates the tiny interest rate of 0.1% because of the continuous nature of their model. Our findings contrast this prediction.

In their paper, Bushong et al. (2021) sketch a model that incorporates insights from the focusing model of Kőszegi and Szeidl (2012) together with their relative thinking approach: focusing plays a role when choices feature more than two dimensions, and relative thinking takes over when there are only two dimensions to consider. In Section 3, we suggest that one could come up with a model that combines our insights alongside those of the focusing model at the stage in which weights are determined. As Kőszegi and Szeidl (2012), Bushong et al. (2021), and the ToD procedure seem to complement each other, it would be interesting to consider a model that is general enough to incorporate all of them together. For example, the weight on a specific dimension may combine the number of alternatives in which that dimension is turned on (as in the ToD procedure) alongside its variance in the choice set. The effect of the variance may depend on the overall number of instances of turned-on dimensions in the choice set in the spirit of the idea raised by Bushong et al. (2021).

Some of our findings may be explained not only through the lens of dimensional weighting. Categories, for example, may be one alternative approach. Models taking this approach describe a decision maker who first forms categories endogenously and then either chooses the best alternative from the most preferred category (Manzini and Mariotti 2012) or picks the best option in each category (Furtado et al. 2019).[19] To illustrate, we follow Manzini and Mariotti (2012) and consider the investment example in Study 1. It is plausible that in the 0-*checking* treatment, an agent divides the set into three categories: liquid, safe, and risky options. Those who care about liquidity may end up choosing the checking account. However, it is also perfectly reasonable that, in the 2-*checking* treatment, the same agent perceives only two categories: safe options and risky ones. If the agent is risk averse, the agent chooses the best option from the first category, which is likely to be the savings plan. Categorization, however, does not seem to apply to the findings from the social preferences study (Study 2) because it does not predict the reversal of ranking between the two unequal splits, which naturally belong to the same category regardless of treatment.

Another channel through which part of our findings may be addressed is choice by iterative search, suggested by Masatlioglu and Nakajima (2013). In their model, the agent starts off with some default option or a reference point in the set. This option generates a consideration set from which the agent picks the best alternative, which replaces the agent's previous reference. The new reference generates another consideration set, and the process goes on until the reference point is the best option in the consideration set, at which point it is chosen. The model is a good fit for online search, which often leads to a list of options that need to be skimmed through sequentially. Applying it to our findings, one would naturally treat the first option we introduce as the default. Suppose that, when it is the 0% checking account (Study 1), the consideration set includes all perfectly liquid options. In this case, only the checking account is considered, and hence, it is chosen. However, when the first option is the 2% checking account, it consists of all safe options, and the agent may end up choosing the savings plan. Once again, as with categories, this approach does not fare well with our findings in Study 2, in which preferences over unaltered options, which are likely to be perceived as belonging to the same consideration set, are reversed.[20]

Other models based on reference points, such as loss aversion (Kahneman and Tversky 1991), may also shed light on our findings but are somewhat harder to apply as they require identifying the reference point from which losses and gains are contemplated. Unlike the iterative search model by Masatlioglu and Nakajima (2013) in which the first alternative is a natural and somewhat technical starting point, as in online search, in models based on loss aversion, identifying the reference point is a much more subtle task (Barberis 2013). Yet, even if we consider the first option as the reference point or the expectation of the participant when starting the questionnaire as in Kőszegi and Rabin (2006), our findings are hard to reconcile with the loss-aversion approach. Consider once again the investment study in which the checking account is enhanced to include a 2% interest rate and suppose that, in the spirit of Kőszegi and Rabin (2006), the reference point's safe-gains dimension is taken as the average of the interest rates of the checking account and savings plan (2% in the 0-*checking* treatment and 3% in the 2-*checking* treatment). Under these assumptions, choosing the 0% checking account would generate larger losses compared with choosing the 2% checking account. At the same time, choosing the savings plan would generate larger gains on that dimension in the 0-*checking* treatment compared with choosing it in the 2-*checking* treatment. As nothing else changes across treatments, no other gain or loss consideration changes either. Thus, the model would predict weakly more choices of the savings plan at the expense of the checking account in the 0-*checking* treatment compared with the 2-*checking* treatment, in contrast to our findings.

To sum up, these theoretical models are able to partially explain our findings, but none of them is able to predict all patterns. We introduce the ToD procedure that draws on the literature on salience and focusing while adding the role of turned-on dimensions to relative weighting. The model generates predictions that are in line with the discontinuous nature of our findings in all three studies. The analysis of participants' explanations provides further support for this procedure.

6. Conclusion

We provide evidence from three different choice contexts for the effect of turning on dimensions on individuals' decision processes and choices. We suggest that turning on a dimension shifts participants' dimensional weights when contemplating alternatives, and as a result, choices are affected in a predictable manner. We show that this effect is, in some cases, strong enough to cause violations of the basic premise of monotonicity in money and may also arise through framing alone. We propose the ToD model that accounts for the discontinuous nature in which turning on dimensions shifts decision weights in our studies.

As a policy implication, we introduce an important yet unknown channel through which checking accounts' interest rates may affect investment behavior. Specifically, it suggests that, by introducing positive interest rates to checking accounts, banks may increase the subjective weight that investors place on safe gains. As a result, a larger proportion of their assets may be allocated to safe investments, such as bonds and CDs, at the expense of their checking account balances. Our findings are also relevant to the design of complex contracts and may potentially be taken into account by firms that try to exploit behavioral consumers (e.g., DellaVigna and Malmendier 2004, Eliaz and Spiegler 2006, Gabaix and Laibson 2006) and by the regulator who may try to counteract such exploitation. Consider, for example, a particular health insurance company that does not provide coverage for a relatively common medical condition, which is covered by its competitors. Our findings suggest that, by offering even partial coverage for other, less probable medical conditions, it would turn them on in the decision makers' minds and, consequently, decrease the weight assigned to the common medical condition on which it underperforms. This may improve its health plan's evaluation compared with the competing companies' plans at a relatively low cost. Another platform for exploiting this phenomenon is multipricing schemes: companies that offer services that span a variety of dimensions, such as banks or cellular phone providers, could price many dimensions at zero, understanding that zero payment for a particular dimension of the service turns it on and masks other dimensions that are highly priced.

These potential applications show the importance of incorporating the role of turned-on dimensions into the decision procedure of different economic agents in the market. A model in which weights are determined by a combination of turned-on dimensions and variance along different dimensions as in the literature on focusing, salience, and relative thinking may enable us to derive sharper predictions of choice in complex environments.

Acknowledgments

The authors thank Neta Klein, Eli Mograbi, Dor Shlenger, Yuval Tsuk, Gilad Bar-Levav, Emily Klinger, and Eliad Amsalem for their great assistance. The authors also thank Ariel Rubinstein, Yair Antler, Dotan Persitz, and Moti Michaeli as well as seminar participants at the Hebrew University, Ben-Gurion University, University of Haifa, Tallinn University of Technology, and participants at The BRIC5 conference, The Second Behavior Change Conference in Coller School of Management, annual meeting of

the Israeli Association of Economics, CESS 15th Anniversary meeting at NYU, 2020 ESA World Meeting, and BREW India 2020 for helpful comments.

Appendix A. Dimension Elicitation in Study 1

As we explain in the main text, there are difficulties in using participants' ex post explanations to learn about the dimensions that they deem relevant for choice at the time of making the decision. In order to assess whether ex post explanations may serve as a proxy for the dimensions that were noticed by participants during the first encounter with the choice set, we ran another experiment. In this experiment, which we elaborate upon in this section, we elicit the dimensions that are relevant for participants without asking them to make a choice. The goals of this experiment are twofold. First, to assess whether the set of dimensions in the ex post explanations is similar to those elicited directly. Our second goal is to examine whether the patterns of differences between the main dimensions that were mentioned in the two treatments are similar across elicitation methods. We first describe the experiment and then the method used to analyze the results. Finally, we compare the dimensions elicited in this experiment to those that were elicited from ex post explanations.

A.1. The Direct Elicitation Experiment

All participants received the same background story regarding the bonus from the workplace as in the main experiment of Study 1 and a brief mention of the potential investment options (the full description of the options only came later to prevent participants from thinking about making a choice). Following the background, participants were informed that they are not asked to choose an investment option. Rather, we asked them to write what, in their opinion, are the most prominent dimensions of each option. Then, participants viewed the options (with their full and detailed descriptions) one by one and were provided space to write the prominent dimensions. As in the main experiment of this study, there were two treatments. The first option in the first treatment was a checking account with no interest rate, and in the second treatment, it was a checking account with a 2% interest rate. The other options in both treatments were a savings plan and a stock with the same characteristics as in the main experiment. We collected data from 223 panelists (different from those who participated in Study 1) who were randomly assigned to one of the two treatments (111 participants in the 0-*checking* treatment and 112 in the 2-*checking* treatment).

A.2. Method of Analysis

In order to obtain the most objective assessment of dimensions mentioned by our participants, we asked for the assistance of two RAs who were not involved in previous text analysis of this project. Both RAs were given the same instructions and worked independently.[21] The instructions to the RAs consisted of the text that was observed by the participants in the experiment. In addition, they were asked to go through the answers, one by one, and write all dimensions that were mentioned by participants as well as to provide a description for each dimension. We explained what a dimension of an option is and the difference between a dimension and a specific value of a dimension (e.g., "blue' is a specific value of the dimension "car color"). After the RAs created their list of dimensions, we asked them to go through the answers again and classify each text entry for each option into the categories of dimensions they created (a text entry of a participant referring to one of the options may be classified into more than one dimension). After the RAs completed their work, we obtained

- Two independent lists of dimensions with their descriptions.
- Two independent distributions of dimensions mentioned for each option in each treatment.

A.3. Results

Table A.1 shows the dimensions listed by the RAs. The first column is the dimension's name (given by the RAs), and the second column consists of a short description. In the last two columns, we mark whether that dimension was mentioned by each of the RAs. The first five rows list the dimensions that were frequently mentioned (*frequent dimensions*), followed by those that were mentioned rarely

Table A.1. Dimensions Mentioned by RAs in the Elicitation Experiment

Dimension	Description	RA-1	RA-2
Risk	Degree of riskiness	✓	✓
Liquidity	Degree of liquidity	✓	✓
Safe gains	Returns due to interest rate	✓	✓
Potential gains	Chance for high gains relative to losses (mostly mentioned with risk)	✓	
High gains	The option involves the possibility for a high gain		✓
Withdrawal procedure	Requirements for money withdrawal	✓	✓
Trust	Level of confidence with respect to financial institution	✓	✓
Background	Current balances/debt and how it affects decision		✓
Offset overdraft	Using the bonus to reduce the overdraft in the checking account	✓	
Spending potential	How likely to wastefully spend money when choosing that option	✓	
Didn't understand	The participant did not understand	✓	✓
Unclear	The text entry did not make sense	✓	✓

(by less than 7% of participants). The last two rows include those who didn't understand what was asked from them (or didn't understand the option) and those who wrote unclear or meaningless texts (we specifically asked the RAs to include these two categories).

Among the frequent dimensions, risk, liquidity, and safe gains were mentioned by both RAs. Potential gains and high gains were mentioned by one but not the other. Looking into these dimensions, we find that they overlap although they are clearly distinct. Within the overlapping region, one can find texts that refer to high possible gains *and* to the chance to end up losing, which were mostly provided with respect to the stock. Looking at the differences between the two dimensions, we find that texts that were classified into the potential-gains dimension referred not only to the gains but also to the relative gain compared with the potential losses, and the high-gains dimension consisted of texts that simply refer to the technical possibility to earn a large sum in that option. Overall, the frequent dimensions are almost identical to those that came up in the ex post explanations of the main experiment. Among those are safe gains and liquidity, which we focus on in the main text, as well as risk and another dimension that evolves around the large earnings presented by the stock. These are also the dimensions that we use to illustrate the prediction of the ToD model in the next section (excluding risk for simplicity).

We now move on to examine the differences in dimensions mentioned across treatments. Note that this elicitation method may lead participants to mention more dimensions compared with the number of dimensions that come to their minds after choosing. The reason is that we explicitly ask participants to write down the prominent dimensions for *each* option. As a result, participants are made to think through every option and may list dimensions that they wouldn't have noticed when only skimming through the choice set on their way to making a choice. Nevertheless, if the enhanced checking account triggers more thoughts about interest rate and safe gains than the 0% checking account, these should be reflected in our comparisons.

Figure A.1 is analogous to Figure 2 in the main text. We average the number of mentions for each dimension and each option across RAs and show the overall mentions of

Figure A.1. (Color online) Dimensions Mentioned per Treatment in the Elicitation Experiment

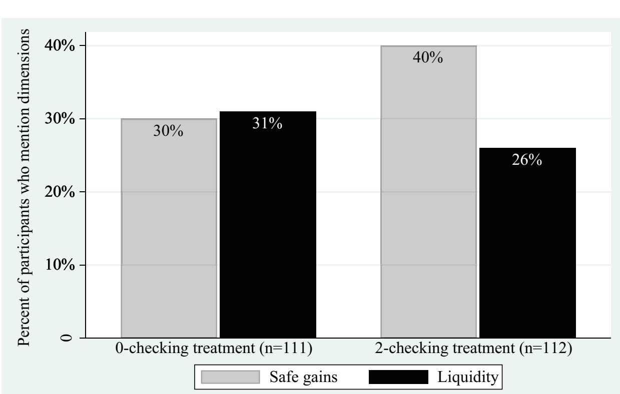


Figure A.2. (Color online) Dimensions of Checking Account per Treatment in the Elicitation Experiment

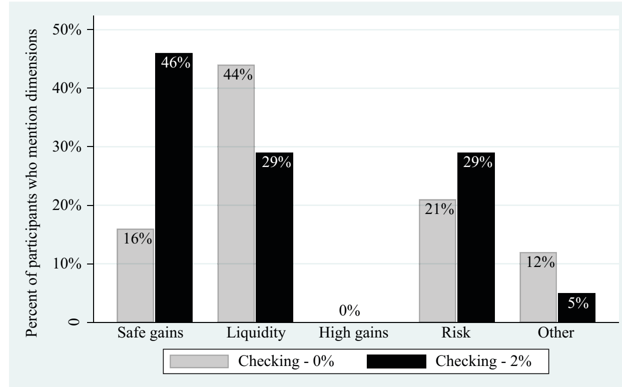


Figure A.3. (Color online) Dimensions of Savings Plan per Treatment in the Elicitation Experiment

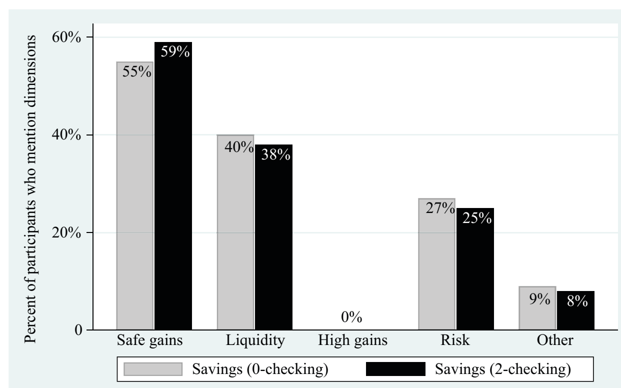
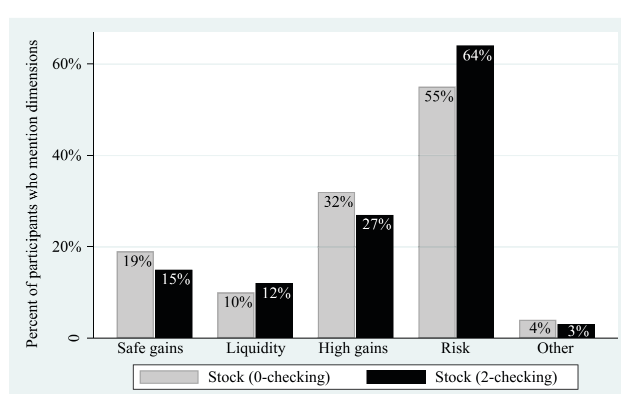


Figure A.4. (Color online) Dimensions of Stock per Treatment in the Elicitation Experiment



the safe gains and liquidity dimensions across treatments.[22] Because participants were asked to write relevant dimensions for each option (unlike in the main experiment in which only one explanation was provided), the percentage was calculated as the overall number of mentions of that dimension in that treatment divided by $3n$, where n is the number of participants in the treatment. Figure A.1 shows similar patterns to those that arise in Figure 2 and reflect the fact that safe gains is more frequently mentioned in the 0-*checking* treatment (p = 0.008). Liquidity is slightly shrouded in the 2-*checking* treatment but not significantly so (p = 0.176). We view this qualitative similarity as supportive evidence for our usage of ex post explanations as a proxy for participants' perceived relevant dimensions.

In Figures A.2–A.4, we examine the distribution of dimensions mentioned in both treatments for the checking account, savings plan, and stock, respectively.[23] In our opinion, Figure A.2 is the most important of the three as it reports the dimensions mentioned for the checking account, which is the only one that was altered across treatments. This figure shows us from where the differences in the previous figure come: safe gains is mentioned more frequently in the enhanced checking account (46% compared with 16%, $p < 0.001$), and liquidity is more frequent in the checking account with no interest rate (44% compared with 29%, $p = 0.023$). The difference in the number of mentions of the other dimensions across the two options is not statistically significant ($p = 0.231$ for the risk dimension and p = 0.089 for "other"). Figures A.3 and A.4 show that the savings plan and the stock were not influenced by the treatment to which they belonged in terms of their perceived prominent dimensions. All differences were not significant according to a chi-square test ($p > 0.199$ for all dimensions).[24]

Appendix B. Explaining the Findings with the ToD Model

Our goal in this section is to show that the ToD model predicts changes in the options' evaluations that are in line with the behavioral patterns observed in our experiments and that these predictions are independent of the specifics of the consumption utilities as long as they are monotonic (and, in the case of Study 1, also continuous). For each study, we first derive the general prediction regarding the directional change of preferences and then choose specific parameter values for which this preference change is strong enough to predict the exact choice pattern that we observed.

B.1. Study 1

There are three available options: *checking*, *savings*, and *stock*. ToD weights are simplified by taking g to be the identity function. We consider the following triplet of dimensions, which appeared most frequently in our participants' explanations: safe gains, liquidity, and the possibility of high returns (higher than 10%).[25] Dimensions are numbered 1, 2, 3, respectively. We assume four "levels" of these dimensions: (0, L, M, H), where zero reflects a zero level of that dimension, L is Low, M is medium, and H is high.

The investment options that appear in the study have the following levels in each dimension: checking— 0% = (0, H, 0), *checking*— 2% = (L, H, 0), savings = (H, L, 0), stock = (0, M, H). In words, both checking accounts have the highest level of liquidity but zero for the possibility of high returns. The account with a 2% interest rate receives a low level in the safe-gains dimension, and the one with 0% interest rate naturally receives zero. The savings plan has a high level of safe gains, low level of liquidity, and zero for high returns. The stock has a medium level of liquidity (better than the savings plan but still requiring a visit or a call to withdraw), a high level for the possibility of high returns, and zero for safe gains.[26]

According to these qualitative dimensional values, each investment option has the following vector of turned-on dimensions: $checking - 0\%^{ToD} = (0,1,0)$, $checking - 2\%^{ToD} = (1,1,0)$, $savings^{ToD} = (1,1,0)$, $stock^{ToD} = (0,1,1)$.

Let us now calculate the dimensional weights in each treatment. Denote the choice set in the 0-*checking* treatment by $No - Int$ and the choice set in the 2-*checking* treatment by $2 - Int$. In the 0-*checking* treatment, the first dimension, safe gains, is only turned on in the savings because that is the only option that has a value larger than zero in that desirable dimension. The number of overall turned-on dimensions in the choice set is five (the *checking*–0% has only liquidity turned on, and the savings and the stock have two turned-on dimensions). Thus, the first dimension's weight is

$$g_1^{ToD}(No - Int) = 1/(1 + 1 + 1 + 1 + 1) = 1/5.$$

Similarly, we obtain

$$g_2^{ToD}(No - Int) = 3/5,\ g_3^{ToD}(No - Int) = 1/5.$$

In the 2-*checking* treatment, the weights are different because of the extra turned-on dimension of the checking account:

$$g_1^{ToD}(2 - Int) = 2/6,\ g_2^{ToD}(2 - Int) = 3/6,\ g_3^{ToD}(2 - Int) = 1/6.$$

We now have all the necessary ingredients for the overall evaluation of every alternative in each treatment. The evaluations in the 0-*checking* treatment are as follows:

$$\tilde{U}(checking - 0\%, No - Int) = 1/5 \cdot u_1(0) + 3/5 \cdot u_2(\mathrm{H}) + 1/5 \cdot u_3(0).$$

Similarly,

$$\tilde{U}(savings, No - Int) = 1/5 \cdot u_1(\mathrm{H}) + 3/5 \cdot u_2(\mathrm{L}) + 1/5 \cdot u_3(0),$$

and

$$\tilde{U}(stock, No - Int) = 1/5 \cdot u_1(0) + 3/5 \cdot u_2(\mathrm{M}) + 1/5 \cdot u_3(\mathrm{H}).$$

Turning to the 2-*checking* treatment, we obtain

$$\tilde{U}(checking - 2\%, 2 - Int) = 2/6 \cdot u_1(\mathrm{L}) + 3/6 \cdot u_2(\mathrm{H}) + 1/6 \cdot u_3(0),$$

$$\tilde{U}(savings, 2 - Int) = 2/6 \cdot u_1(\mathrm{H}) + 3/6 \cdot u_2(\mathrm{L}) + 1/6 \cdot u_3(0),$$

and

$$\tilde{U}(stock, 2 - Int) = 2/6 \cdot u_1(0) + 3/6 \cdot u_2(\mathrm{M}) + 1/6 \cdot u_3(\mathrm{H}).$$

We now examine the differences in the evaluations of the checking account and savings plan resulting from the introduction of the 2% interest rate. For simplicity and without loss of generality, we make one assumption on the consumption utility values, which is $u_i(0) = 0,\ \forall i$. The increase in the evaluation of the savings plan equals $4/30 \cdot u_1(\mathrm{H}) - 3/30 \cdot u_2(\mathrm{L})$. The first term is the added value resulting from the increase in the weight of the safe-gains dimension; the second term is due to the decrease in the weight of the liquidity dimension. A similar calculation shows that the increase in the evaluation of the checking account amounts to $2/6 \cdot u_1(\mathrm{L}) - 3/30 \cdot u_2(\mathrm{H})$. Finally, the evaluation of the stock is increased by $-3/30 \cdot u_2(\mathrm{M}) - 1/30 \cdot u_3(\mathrm{H})$. Thus, if the interest rate is low enough (and u_1 continuous as we assumed), the increase in the evaluation of the savings plan outweighs that of the checking account (and the stock) and pushes it in the direction of our observed preference reversal. Reflecting on Study 1 and the participants' frequent mention of safe gains in the enhanced 2-*checking* treatment, we argue that this describes the actual weight shift of prominent dimensions for at least some participants.

Moving on to our numerical example, we further assume that the decision maker appreciates high safe gains and does not need the money right now so that a high level of the first dimension is more valuable to the decision maker than a high level in one of the other dimensions. Thus, for dimension $1: u_1(0) = 0,\ u_1(\mathrm{L}) = 1, u_1(\mathrm{H}) = 5$. For dimension 2, we have $u_2(L) = 1,\ u_2(\mathrm{M}) = 2, u_2(\mathrm{H}) = 3$, and for dimension $3: u_3(0) = 0,\ u_3(\mathrm{H}) = 2$.

Given the dimensional weights that we calculated, the evaluations in the 0-*checking* treatment are as follows:

$$\tilde{U}(checking - 0\%, No - Int) = 1/5 \cdot u_1(0) + 3/5 \cdot u_2(\mathrm{H}) + 1/5 \cdot u_3(0) = 1/5 \cdot 0 + 3/5 \cdot 3 + 1/4 \cdot 0 = 9/5.$$

Similarly,

$$\tilde{U}(savings, No - Int) = 1/5 \cdot 5 + 3/5 \cdot 1 + 1/5 \cdot 0 = 8/5,$$

and

$$\tilde{U}(stock, No - Int) = 1/5 \cdot 0 + 3/5 \cdot 2 + 1/5 \cdot 2 = 8/5.$$

Thus, an agent described by the ToD procedure with these consumption utilities' values chooses the checking account in the 0-*checking* treatment. Turning to the 2-*checking* treatment, we obtain

$$\tilde{U}(checking - 2\%, 2 - Int) = 11/6,$$
$$\tilde{U}(savings, 2 - Int) = 13/6,\ \tilde{U}(stock, 2 - Int) = 8/6,$$

and we observe a choice reversal that is an apparent violation of monotonicity. Looking at the numbers, it is evident that the checking account is not made worse because of its additional interest rate. In fact, its overall utility goes up from 9/5 to 11/6. However, the shift of weights also leads to an increase in the overall utility of the savings plan. These forces pull the relative attractiveness of the two options in opposite directions, and according to our utility specification, the latter prevails. As shown earlier, the relative change in utilities operates in the direction of our observed behavioral pattern for any choice of consumption utility values as long as the interest rate added to the checking account is small enough and consumption utilities are monotonic and continuous in every dimension.[27]

B.2. Study 2

ToD weights are simplified by taking g to be the identity function. We naturally consider the undesirable inequality dimension (dimension 1) alongside the desirable efficiency dimension (dimension 2), which were the two dimensions that participants referred to most frequently in their explanations. We assume five possible levels (0, VL, L, M, H) of these dimensions: VL reflects a very low level of that dimension, L is low, M is medium, and H is high. Here are the levels along each dimension of the options that appeared in the study: (100, 100) = (0, VL), that is, zero in dimension 1 (inequality) and VL in dimension 2 (efficiency); (100, 130) = (L, L); (100, 140) = (M, M); (100, 160) = (H, H). In words, the level of both inequality and efficiency is lowest for (100, 100) and increases with the payoff for the other participant. Notice that the level of the desirable dimension of efficiency is above zero in every alternative (as they all allocate an overall substantial amount to the participants) and, hence, turned on in each alternative although the undesirable dimension of inequality is only turned on in the (100, 100) split that has a zero level along that dimension. Thus, for these qualitative dimensional values, each option has the following vector of turned-on dimensions:

$$(100{,}100)^{ToD} = (1, 1),$$
$$(100{,}130)^{ToD} = (100{,}140)^{ToD} = (100{,}160)^{ToD} = (0, 1).$$

Let us now calculate the dimensional ToD weights. Denote the choice set in the *unequal* treatment by U and in the *equal* treatment by E. In the equal treatment, dimension 1 (inequality) is only turned on in one option although there are overall four instances of turned-on dimensions in the set (both dimensions are turned on in (100, 100), and only efficiency is turned on in the other allocations). Hence, the dimensional weights are

$$g_1^{ToD}(\mathrm{E}) = 1/(1 + 1 + 1 + 1) = 1/4,\ g_2^{ToD}(\mathrm{E}) = 3/4.$$

In the unequal treatment, the weights are different because the inequality dimension is completely turned off. The weights are

$$g_1^{ToD}(\mathrm{U}) = 0/3,\ g_2^{ToD}(\mathrm{U}) = 3/3.$$

We now have all the necessary ingredients for the overall evaluation of every alternative in each treatment. The evaluations in the *equal* treatment are as follows:

$$\tilde{U}((100, 100), E) = 1/4 \cdot u_1(0) + 3/4 \cdot u_2(\mathrm{VL}) \quad .$$

Similarly,

$$\tilde{U}((100, 140), E) = 1/4 \cdot u_1(\mathrm{M}) + 3/4 \cdot u_2(\mathrm{M})$$

and

$$\tilde{U}((100, 160), E) = 1/4 \cdot u_1(\mathrm{H}) + 3/4 \cdot u_2(\mathrm{H}),$$

and given the ToD weights in the unequal treatment, we obtain

$$\tilde{U}((100, 130), U) = 3/3 \cdot u_2(\mathrm{L}),$$
$$\tilde{U}((100, 140), U) = u_2(\mathrm{M}),\ \tilde{U}((100, 160), U) = u_2(\mathrm{H}).$$

Thus, moving from the *unequal* treatment to the equal treatment, the difference in the evaluation of (100, 160) amounts to

$$\Delta(\tilde{U}) = 1/4 \cdot u_1(\mathrm{H}) - 1/4 \cdot u_2(\mathrm{H}),$$

and the difference in the evaluation of (100, 140) equals

$$\Delta(\tilde{U}) = 1/4 \cdot u_1(M) - 1/4 \cdot u_2(\mathrm{M}).$$

Given that dimension 1 is undesirable and dimension 2 is desirable, it is evident that the second expression is larger than the first for any choice of monotonic consumption utilities. Thus, the evaluation of (100, 140) increases by more than the evaluation (100, 160). In other words, the model qualitatively pushes the relative ranking between (100, 140) and (100, 160) in favor of the former when the (100, 130) allocation is replaced with the all-equal (100, 100) split. Highlighting the inequality dimension by replacing (100, 130) with the all-equal split alongside the shrouding of the efficiency dimension is the driving force behind this qualitative effect.

We now provide a numerical example that generates an actual reversal between the two unequal allocations. We assume that the decision maker cares about inequality more than efficiency in terms of their intrinsic influence on well-being. Thus, $u_1(\mathrm{H}) = 0$, $u_1(\mathrm{M}) = 4, u_1(\mathrm{L}) = 8$, $u_1(0) = 12$, and $u_2(VL) = 1$, $u_2(\mathrm{L}) = 2, u_2(\mathrm{M}) = 3$, $u_2(\mathrm{H}) = 4$. Given the ToD weights that we have already calculated, the evaluations in the *unequal* treatment are as follows:

$$\tilde{U}((100,130),U) = 2,\ \tilde{U}((100,140),U) = 3,\ \tilde{U}((100,160),U) = 4.$$

Hence, an agent in the *unequal* treatment who abides by the ToD procedure and has the preceding consumption utility values ranks the option (100, 160) first, followed by (100, 140) and (100, 100). Moving on to the equal treatment, the evaluations are as follows:

$$\tilde{U}((100,100),E) = 1/4 \cdot u_1(0) + 3/4 \cdot u_2(\mathrm{VL}) = 1/4 \cdot 12 + 3/4 \cdot 1 = 15/4.$$

Similarly,

$$\tilde{U}((100,140),E) = 1/4 \cdot 4 + 3/4 \cdot 3 = 13/4,$$

and

$$\tilde{U}((100,160),E) = 1/4 \cdot 0 + 3/4 \cdot 4 = 12/4.$$

We see that, in the equal treatment, the rankings are reversed in line with our findings for a significant percentage of participants.[28]

B.3. Study 3

As in the case of the previous studies, ToD weights are simplified by taking g to be the identity function. We consider three dimensions: the known probability of receiving a prize of 95 ILS (dimension 1), receiving at least 50 ILS with certainty (dimension 2), and the possibility to win a prize above 100 ILS (dimension 3).[29] The study focuses on the first two dimensions: the high prize of 95 ILS is explicitly mentioned in *a*' but not in *a*, and certainty is mentioned in the description of option *a* but not in *a*'. We assume three levels (0, L, H) of the first dimension and two (0, H) for the other discrete dimensions, where zero reflects a zero level of that dimension, L is low, and H is high. The following are the options' levels along the different dimensions: a = (L,H,0), a' = (L, H, 0), b = (H, 0, 0), and c = (0, 0, H).

Here is an explanation for the choices of different levels for each option: *a* and *a*' are exactly the same, so they have identical levels in all dimensions. Specifically, they have a low probability (14%) of winning the prize of 95 ILS, a prize larger than 50 ILS with certainty, and no chance of obtaining a prize higher than 100 ILS. Option *b* has a high probability (50%) of winning the prize of 95 ILS but a certain prize of only 40 ILS and, as *a* and *a*', does not offer any prize above 100 ILS. Option *c* is a bet with unknown probabilities; hence, it receives a level of zero in the first dimension. Its minimal prize is smaller than 50 ILS, but it does offer a prize that exceeds 100 ILS if the Dow–Jones Index goes up. Keep in mind that this study deals with framing so that an alternative may have a positive level in some dimension that is still not noticed by the decision maker because it is not explicitly mentioned in the description of the alternative. Given the manner in which alternatives are described in the study, each option has the following vector of turned-on dimensions:

$$a^{ToD} = (0,1,0),\ a'^{ToD} = (1,0,0),\ b^{ToD} = (1,0,0),\ c^{ToD} = (0,0,1).$$

In other words, dimension 1 is turned on when the prize of 95 ILS is explicitly mentioned alongside its probabilities, that is, in options *a*' and *b* (it is turned off in *a* despite its positive value because the decision maker is likely not to think about a prize of 95 ILS given the framing of *a*). Dimension 2, the prize of at least 50 ILS with certainty, is turned on only in *a* because it is the only alternative that is described using the words "with certainty." Alternative *c* is the only one in the set that has dimension 3 turned on, and that is its only turned-on dimension.

Given these vectors, ToD weights in the *certain*(3) treatment are the following:

$$g_1^{ToD} = (1)/(1+1+1) = 1/3, g_2^{ToD} = 1/3,\ g_3^{ToD} = 1/3.$$

In the *lottery*(3) treatment, the second dimension is turned off in all alternatives. The dimensional weights are, therefore, equal to

$$g_1^{ToD} = 2/3,\ g_2^{ToD} = 0/3,\ g_3^{ToD} = 1/3.$$

We now have all the necessary ingredients for the overall evaluation of every alternative in each treatment. In *certain*(3),

$$\tilde{U}(a,\{a,b,c\}) = 1/3 \cdot u_1(\mathrm{L}) + 1/3 \cdot u_2(\mathrm{H}) + 1/3 \cdot u_3(0).$$

Similarly,

$$\tilde{U}(b,\{a,b,c\}) = 1/3 \cdot u_1(\mathrm{H}) + 1/3 \cdot u_2(0) + 1/3 \cdot u_3(0)$$

and

$$\tilde{U}(c,\{a,b,c\}) = 1/3 \cdot u_1(0) + 1/3 \cdot u_2(0) + 1/3 \cdot u_3(\mathrm{H}).$$

Turning to the *lottery*(3) treatment, we obtain

$$\tilde{U}(a',\{a',b,c\}) = 2/3 \cdot u_1(\mathrm{L}) + 0 \cdot u_2(\mathrm{H}) + 1/3 \cdot u_3(0),$$

$$\tilde{U}(b,\{a',b,c\}) = 2/3 \cdot u_1(\mathrm{H}) + 0 \cdot u_2(0) + 1/3 \cdot u_3(0),$$

and

$$\tilde{U}(c,\{a',b,c\}) = 2/3 \cdot u_1(0) + 0 \cdot u_2(0) + 1/3 \cdot u_3(\mathrm{H}).$$

Moving from *certain*(3) to *lottery*(3), the difference in the evaluation of b equals $1/3 \cdot u_1(\mathrm{H})$, which is strictly positive regardless of the choice of utility values.[30] Thus, the ToD procedure predicts that it will have a higher evaluation because of the change of frame of the first option. The change in the evaluation of the first option, on the other hand, equals $1/3 \cdot u_1(\mathrm{L}) - 1/3 \cdot u_2(\mathrm{H})$, which a priori may be positive or negative. However, if the known probability of obtaining the high prize of 95 ILS (dimension 1) is small enough and given our continuity assumption, the overall evaluation of the first alternative will not increase, and the model's prediction is in line with our reported choice reversal.

For the purpose of the numerical example, we assume that the decision maker has the following evaluations along the three dimensions: $u_1(0) = 0$, $u_1(\mathrm{L}) = 7, u_1(\mathrm{H}) = 9$, $u_2(0) = 0, u_2(\mathrm{H}) = 3$, and $u_3(0) = 0, u_3(\mathrm{H}) = 5$. Given the dimensional weights we calculated earlier, we may now calculate the evaluations of every alternative in each treatment. In *certain*(3),

$$\tilde{U}(a, \{a, b, c\}) = 1/3 \cdot u_1(\mathrm{L}) + 1/3 \cdot u_2(\mathrm{H}) + 1/3 \cdot u_3(0) = 1/3 \cdot 7 + 1/3 \cdot 3 + 1/3 \cdot 0 = 10/3.$$

Similarly,

$$\tilde{U}(b, \{a, b, c\}) = 1/3 \cdot 9 + 1/3 \cdot 0 + 1/3 \cdot 0 = 9/3,$$

and

$$\tilde{U}(c, \{a, b, c\}) = 1/3 \cdot 0 + 1/3 \cdot 0 + 1/3 \cdot 5 = 5/3.$$

Such an agent would choose a in the *certain*(3) treatment. Turning to the *lottery*(3) treatment, we obtain

$$\tilde{U}(a', \{a', b, c\}) = 2/3 \cdot 7 = 14/3,\ \tilde{U}(b, \{a', b, c\}) = 18/3,\ \tilde{U}(c, \{a', b, c\}) = 5/3.$$

Thus, the change of frame shifts an individual described by the ToD model with the preceding utility values from choosing a in the *certain*(3) treatment to choosing b in treatment *lottery*(3). Although the first option does not change per se, the lottery framing with its explicit mention of the prize of 95 ILS turns on the first dimension that was turned off in the certain payment framing. At the same time, the certain payoff is no longer mentioned in *lottery*(3), and as a result, the dimension on which the first option performs well—dimension 2—receives no weight. Overall, a higher weight is given to the first dimension and a lower weight to the second dimension. Given our choices of utility values, option b benefits the most from this shift in weights because it performs best along the dimension with the bumped-up weight. The first option gains from the increased weight of the first dimension but is hurt from the reduced weight of the second dimension. Overall, its evaluation increases but to a lesser extent than the evaluation of b which is now the highest in the set.

To complete the picture, we show how the model with these specific utility values explains the findings from treatment *certain*(2) and *lottery*(2). In the former, weights are given by

$$g_1^{ToD} = 0,\ g_2^{ToD} = g_3^{ToD} = (1)/(1+1) = 1/2,$$

and in treatment *lottery*(2),

$$g_2^{ToD} = 0,\ g_1^{ToD} = g_3^{ToD} = 1/2.$$

With these weights, we obtain the following evaluations. In *certain*(2),

$$\tilde{U}(a, \{a, c\}) = 1/2 \cdot u_2(\mathrm{H}) + 1/2 \cdot 0 = 3/2,$$

and

$$\tilde{U}(c, \{a, c\}) = 5/2.$$

On the other hand, in treatment *lottery*(2) we obtain

$$\tilde{U}(a', \{a', c\}) = 7/2,\ \tilde{U}(c, \{a', c\}) = 5/2.$$

In the absence of b, dimension 1 receives zero weight in treatment *certain*(2), and dimension 2 receives zero weight in treatment *lottery*(2). According to our numerical example, when a is replaced by a' and turns on the first dimension, this leads to a relatively large shift in the evaluation of the first option. At the same time, dimension 3 receives the same weight across treatments, and hence, the evaluation of option c is unchanged. This leads to the pattern we observe across these binary choice treatments: a higher proportion of participants choosing the first option in the *lottery*(2) treatment.

Appendix C. Questionnaires

These are the English translations for the instructions of the main experiments of all studies (the instructions were originally written in Hebrew as the experiment was run in Israel). The wording of the parallel treatment is reported in square brackets.

C.1. Study 1: Instructions of the 2-*Checking* (0-*Checking*) Treatment

C.1.1. Decision-Making Questionnaire: General Instructions.

1. Thank you for agreeing to participate in a brief decision-making experiment. The experiment includes just a few questions and is expected to take a few minutes to complete.
2. The questions are phrased in masculine form but are addressed to women and men alike.
3. The questionnaire deals with your preferences, and therefore, there are no right or wrong answers.
4. The questions describe hypothetical situations in which you are asked to choose between several options. For the success of the experiment, we ask that you answer the questions sincerely.[31]
5. The experiment is completely anonymous.

Question 1

Imagine that you are an employee in a firm. At the beginning of the new year, your employer informs you that you, as well as the other employees, are about to receive a bonus of 10,000 ILS. This bonus will be deposited for you by your employer in one of three options. Which one would you choose?

a. In your checking account, which generates a 2% yearly interest rate with certainty. [which does not generate any interest.]

* Some checking accounts in Israel have interest and some do not. Please assume for this questionnaire that your account has a 2% interest [no interest] even if this is not the case in reality.

b. In a savings plan, which generates a 4% yearly interest rate with certainty.

* The account has weekly exit options, in which you can withdraw the money by making a request online or by phone.

c. In a stock that can gain or lose with a 50–50 chance. If it goes up, it earns 14% a year; if it goes down, it loses 5% a year.

* The stock can be sold any time by making a request online or by phone.

Note: If the amount (or part of it) is withdrawn before an entire year has passed, you will receive the proportional share of the annual profits. At the end of each year, the remaining balance on your chosen track will remain on the same track under the same conditions unless you specify otherwise.

Question 2

Please briefly explain your choice: ______________

Question 3*

***Comment.** The results of this question are not discussed in the body of the paper.

Now imagine that the situation is the same as described in Question 1, only that now the employer asks you to choose the percentage of the amount of 10,000 ILS that you would like to deposit in each option. Note that the sum of the percentages must equal 100. What is the percentage you would like to allocate to each option?

a. In your checking account, which generates a 2% yearly interest rate with certainty. [which does not generate any interest.] _____

b. In a savings plan, which generates a 4% yearly interest rate with certainty. _____

c. In a stock that can gain or lose with a 50–50 chance. If it goes up, it earns 14% a year; if it goes down, it loses 5% a year. _____

Please briefly explain your choice: _________________

C.2. Study 2: Instructions of the Equal [Unequal] Treatment

C.2.1. Decision Making Questionnaire: General Instructions.

1. Thank you for agreeing to participate in a brief decision-making experiment. The experiment includes two questions and is expected to take a few minutes to complete.

2. The questions are phrased in masculine form but are addressed to women and men alike.

3. The questionnaire deals with your preferences, and therefore, there are no right or wrong answers.

4. In this questionnaire, there is a possibility of winning a significant amount of money. At the end of the experiment (in about two days), 5% of those who complete the entire questionnaire will be randomly drawn to receive prizes according to their choices. Please note that this payment is on top of the participation fee, which you will receive for filling out the questionnaire.[32] At the moment, it is impossible to know which of the participants will be drawn for payment, and therefore, it is recommended to answer according to your true preferences. Those who will be drawn to receive the additional payment will be notified of their prize via email.

5. The experiment is completely anonymous.

Question 1

Assume that you have been selected for payment. Chosen alongside you is another participant that you do not know (who will also complete the questionnaire). You are asked to determine the payment for both of you. There are three options:

a. 100 ILS for you and 100 ILS for the other participant. [100 ILS for you and 130 ILS for the other participant.]

b. 100 ILS for you and 140 ILS for the other participant.

c. 100 ILS for you and 160 NIS for the other participant.

Please rank the options according to your preferences: 1 - the option you prefer the most, 2 - the option that is ranked 2nd according to your preferences, 3 - the option that you prefer the least.

You and the other participant will not know anything about each other's identity.

Note: For payment purposes, the option you rank highest will be selected with a 60% chance and the option you rank second will be chosen with a 40% chance. Therefore, it is recommended that you rank all three options according to your true preferences.

a. 100 ILS for you and 100 ILS for the other participant. [100 ILS for you and 130 ILS for the other participant.] _____

b. 100 ILS for you and 140 ILS for the other participant. _____

c. 100 ILS for you and 160 NIS for the other participant. _____

Question 2

Please briefly explain your choice: ___________________ __________

C.3. Study 3: Instructions of the Certain(3) [Lottery(3)] Treatment

These are the instructions for treatments *certain*(3) and *lottery*(3). The instructions for treatment *certain*(2) and *lottery*(2) are identical except that option (b) is excluded.

C.3.1. Decision Making Questionnaire: General Instructions.

1. Thank you for agreeing to participate in a short experiment that includes two questions and is expected to take a few minutes.

2. The questions are phrased in masculine form but are addressed to women and men alike.

3. The experiment is anonymous. You are only requested to specify your gender, your major, and age range. In addition, we ask you to type your email address, which will be used only to update you if you won a prize.

4. The questionnaire deals with your preferences, and therefore, there are no right or wrong answers.

5. If you have any questions or comments, please send an email to Ayala Arad from Tel Aviv University (aradayal@post.tau.ac.il).

6. As you will shortly see, the experiment describes a choice between several options that entitle you to significant amounts of money. As soon as the experiment ends (it will end in a couple of days), 5% of those who fill out the entire questionnaire will be randomly drawn to receive the money amount according to their choice. We will send an email to the winners and explain where they can receive their payment. Payment can also be received through Bit and Pepper Pay payment applications.

7. At the moment, it is impossible to know which of the participants will be drawn for payment, and therefore, it is recommended to address the question as if you will really receive your chosen option.

Email (to be used only to notify you if you won a prize): ________________________

Gender:
- Male
- Female

Age:
- 18–25
- 26–35
- 36–45
- 46+

Major: ________________________

Question 1

You are facing the following three options. Which one would you like to choose?

a. Receive 60 ILS with certainty. On top of this amount, you will receive an additional 35 ILS if you win in a lottery that will be performed by the computer (a 14% chance). [Participate in the following computer lottery: A 14% chance to receive 95 ILS and an 86% chance to receive 60 ILS.]

b. Participate in the following computer lottery: A 50% chance to receive 95 ILS and a 50% chance to receive 40 ILS.

c. Participate in the following gamble on the stock market: If the Dow Jones Industrial Average Index at the end of the next trading day is higher than at the beginning of that day you will receive 115 ILS. If it drops, you will receive 30 ILS (the probability that the index will increase/decrease is not known).

Note: The Dow Jones Industrial Average Index is a stock market index that shows how 30 large publicly owned companies based in the United States have recently traded.

Question 2

Please briefly explain your choice: ____ ____________

Endnotes

[1] In this literature, the term "attributes" is used to describe alternatives' characteristics. Later, we explain the difference between attributes and dimensions and the reason for our using the latter throughout the paper.

[2] See Frederick et al. (2014) for a critical view and Huber et al. (2014) for a response.

[3] Lombardi (2009) and de Clippel and Eliaz (2012) propose two theoretical approaches that hinge on these ideas.

[4] Recently, Zhang and Slovic (2019) show a similar affect with respect to options that include the possibility of no deaths in the context of life-saving decisions.

[5] Note that even in the binary choice contexts of the zero-effect findings, the predictions of our model may differ from those in that literature and sometimes even point in opposite directions. For example, according to Palmeira (2010), a credit card company is better off offering student cards with a low annual percentage rate rather than zero if another issuer offers student cards with a large annual percentage rate. By contrast, the ToD model suggests that a rate of zero would turn on the interest rate dimension (which is obviously undesirable), increasing the credit card company's share of student customers as a result.

[6] The psychological literature on priming is vast. See Cohn and Maréchal (2016) for a review of priming in incentivized economic experiments.

[7] Consider, for example, shopping for a camera in a department store. Although the price, number of megapixels, and storage space may be provided by the manufacturer (among other technical attributes), the feel of the camera and its ergonomic design are difficult to quantify and will not appear in the camera's technical description. Nonetheless, these aspects are likely to be taken into consideration by an amateur photographer.

[8] In fact, our experiments are also not meant to inform us about actual decision weights. They provide a qualitative assessment of the dimensional weights and how they are affected by turning on dimensions in the choice set.

[9] See Dertwinkel-Kalt et al. (2017, 2021) and Dertwinkel-Kalt and Köster (2015) for experimental support of these models.

[10] In the second question, they were asked to choose the proportion of the bonus that they wanted to allocate to each option. The answers to this question give rise to the same behavioral patterns that shows up in question 1. The full questionnaire is available in Appendix C.1.

[11] This procedure was held for each of the three studies reported in the paper. In this study, the RAs' classifications were aligned along 84% of the cases. In the second and third studies, unanimous agreement was reached along 91% and 85% of the cases, respectively.

[12] Similar differences were obtained in the 0.1% experiment. Safe gains was mentioned by 13% in the 0-*checking* treatment and by 28% in the 0.1-*checking* treatment ($p = 0.006$). Liquidity was mentioned by 14% in the 0-*checking* treatment compared with 6% in the 0.1-*checking* treatment ($p = 0.057$).

[13] The complete questionnaire appears in Appendix C.2.

[14] This is the only study in which rankings were elicited rather than choices. In our opinion, choosing is more natural than ranking, and we, therefore, designed choice tasks in studies 1 and 3. In this study we couldn't rely on choices because our main interest lies in the relative ranking of options b and c. If some participants who rank b over c would choose option a' (which is likely for participants who ranked $a' > b > c$), this would compromise our ability to detect the behavioral pattern we expect.

[15] Overall, looking at both treatments together, 92% of the rankings were monotone, that is, from the most efficient allocation to the least efficient one (70%) or vice versa (22%). Thus, the vast majority of participants who ranked the first allocation on top actually ranked (a or a') $> b > c$ (87 out of 104). Out of the 278 participants who ranked c on top, 276 ranked $c > b >$ (a or a').

[16] The complete questionnaire appears in Appendix C.3.

[17] Kőszegi and Szeidl (2012) discuss potential framing effects in the context of intertemporal choice and suggest that the explicit mention of the time intervals of a payment may change the perspective through which the consumer views the future transactions. In fact,

our view of framing effects in the context of turned-on dimensions follows their footsteps and as do Kőszegi and Szeidl (2012), we believe that this is an important venue for future work.

[18] Azar (2007) offers another approach to relative thinking. For experimental evidence of relative thinking see, for example, Azar (2011).

[19] For other approaches involving categories and reference points see Barbos (2010) and Maltz (2020).

[20] For another approach involving consideration sets formed by an endogenous reference point, see Ok et al. (2015).

[21] The instructions given to the RAs are available upon request.

[22] There were no significant differences across RAs in the percentages of mentions for each dimension of each option (the potential gains of RA-1 was compared with the high gains of RA-2 because these dimensions had a significant overlap as discussed. These two dimensions were also averaged with each other). The highest difference between the RAs among the frequent dimensions was 7% (in 21 out of 24 instances, it was actually less than 4%). Given that these differences were very small, we show their averages in the next tables rather than looking at each RA's distributions at a time.

[23] As in Figure A.1, we present the average (over RAs) of the percentage of mentions of each dimension for each option.

[24] In Figures A.2–A.4, all dimensions that were not frequently mentioned were grouped together and named "other." These figures also ignore all answers that were unclear or in which the participant did not understand the task.

[25] For simplicity and without loss of generality, we exclude the risk dimension that was also mentioned frequently by our participants.

[26] All options are liquid to some extent as they allow withdrawing the money within, at most, a week. A value of zero liquidity in our study would fit an option that does not allow withdrawals for a prolonged period of time, say, one year.

[27] Using the same consumption utility values in the two-option experiment, the evaluation of the checking account increases relative to the stock when it carries a positive interest rate.

[28] In the no-equality experiment, there are no differences in evaluations across treatments because the same dimensions are turned on in both of them.

[29] For simplicity, we use only these dimensions although others, such as expectations and risk, were also referred to by our participants.

[30] We assume once again that $u_i(0) = 0,\ \forall i$. In this exercise, this assumption does entail some loss of generality. Without it, we would need to require that, for a small enough known probability of obtaining the high prize of 95 ILS (dimension 1), the term $[1/3 \cdot u_1(\mathrm{H}) - 1/3 \cdot u_2(0)]$ is greater than the term $[1/3 \cdot u_1(\mathrm{L}) - 1/3 \cdot u_2(\mathrm{H})]$.

[31] Participants received a flat rate of 5 ILS for completing the questionnaire, but that was not iterated in the instructions as it was communicated through their user account in the panel company.

[32] Participants received a flat rate of 3 ILS for completing the questionnaire, but that was not iterated in the instructions as it was communicated through their user account in the panel company.

References

Ariely D, Wallsten TS (1995) Seeking subjective dominance in multidimensional space: An explanation of the asymmetric dominance effect. *Organ. Behav. Human Decision Processes* 63(3):223–232.

Azar OH (2007) Relative thinking theory. *J. Socio-Economics* 36(1):1–14.

Azar OH (2011) Do people think about absolute or relative price differences when choosing between substitute goods? *J. Econom. Psych.* 32(3):450–457.

Barberis NC (2013) Thirty years of prospect theory in economics: A review and assessment. *J. Econom. Perspect.* 27(1):173–196.

Barbos A (2010) Context effects: A representation of choices from categories. *J. Econom. Theory* 145(3):1224–1243.

Bargh JA, Chartrand TL (2000) The mind in the middle: A practical guide to priming and automaticity research. Reis HT, Judd CM, eds. *Handbook of Research Methods in Social and Personality Psychology* (Cambridge University Press, Cambridge, UK), 253–285.

Bateman I, Dent S, Peters E, Slovic P, Starmer C (2007) The affect heuristic and the attractiveness of simple gambles. *J. Behav. Decision Making* 20(4):365–380.

Bordalo P, Gennaioli N, Shleifer A (2013) Salience and consumer choice. *J. Political Econom.* 121(5):803–843.

Bushong B, Rabin M, Schwartzstein J (2021) A model of relative thinking. *Rev. Econom. Stud.* 88(1):162–191.

Charness G, Rabin M (2002) Understanding social preferences with simple tests. *Quart. J. Econom.* 117(3):817–869.

Cheng-Ming J, Hong-Mei S, Long-Fei Z, Zhao L, Hong-Zhi L, Hong-Yue S (2017) Better is worse, worse is better: Reexamination of violations of dominance in intertemporal choice. *Judgment Decision Making* 12(3):253–259.

Cohn A, Maréchal MA (2016) Priming in economics. *Current Opinion Psych.* 12:17–21.

de Clippel G, Eliaz K (2012) Reason-based choice: A bargaining rationale for the attraction and compromise effects. *Theoret. Econom.* 7(1):125–162.

DellaVigna S, Malmendier U (2004) Contract design and self-control: Theory and evidence. *Quart. J. Econom.* 119(2):353–402.

Dertwinkel-Kalt M, Köster M (2015) Violations of first-order stochastic dominance as salience effects. *J. Behav. Experiment. Econom.* 59:42–46.

Dertwinkel-Kalt M, Köhler K, Lange MR, Wenzel T (2017) Demand shifts due to salience effects: Experimental evidence. *J. Eur. Econom. Assoc.* 15(3):626–653.

Dertwinkel-Kalt M, Gerhardt H, Riener G, Schwerter F, Strang L (2021) Concentration bias in intertemporal choice. *Rev. Econom. Stud.*, ePub ahead of print September 27, https://doi.org/10.1093/restud/rdab043.

Dhar R, Glazer R (1996) Similarity in context: Cognitive representation and violation of preference and perceptual invariance in consumer choice. *Organ. Behav. Human Decision Processes* 67(3):280–293.

Doyle JR, O'Connor DJ, Reynolds GM, Bottomley PA (1999) The robustness of the asymmetrically dominated effect: Buying frames, phantom alternatives, and in-store purchases. *Psych. Marketing* 16(3):225–243.

Eliaz K, Spiegler R (2006) Contracting with diversely naive agents. *Rev. Econom. Stud.* 73(3):689–714.

Fehr E, Schmidt KM (1999) A theory of fairness, competition, and cooperation. *Quart. J. Econom.* 114(3):817–868.

Frederick S, Lee L, Baskin E (2014) The limits of attraction. *J. Marketing Res.* 51(4):487–507.

Furtado BA, Nascimento L, Riella G (2019) Rational choice with full-comparability domains. Working paper, Columbia University, New York.

Gabaix X, Laibson D (2006) Shrouded attributes, consumer myopia, and information suppression in competitive markets. *Quart. J. Econom.* 121(2):505–540.

Gneezy U, Rey-Biel P (2014) On the relative efficiency of performance pay and noncontingent incentives. *J. Eur. Econom. Assoc.* 12(1):62–72.

Gneezy U, List JA, Wu G (2006) The uncertainty effect: When a risky prospect is valued less than its worst possible outcome. *Quart. J. Econom.* 121(4):1283–1309.

Hedgcock W, Rao AR, Chen H (2009) Could Ralph Nader's entrance and exit have helped Al Gore? The impact of decoy dynamics on consumer choice. *J. Marketing Res.* 46(3):330–343.

Huber J, Payne JW, Puto C (1982) Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *J. Consumer Res.* 9(1):90–98.

Huber J, Payne JW, Puto C (2014) Let's be honest about the attraction effect. *J. Marketing Res.* 51(4):520–525.

Kahneman D, Tversky A (1991) Loss aversion in riskless choice: A reference dependent model. *Quart. J. Econom.* 106(4):1039–1061.

Kivetz R, Simonson I (2000) The effects of incomplete information on consumer choice. *J. Marketing Res.* 37(4):427–448.

Kőszegi B, Rabin M (2006) A model of reference-dependent preferences. *Quart. J. Econom.* 121(4):1133–1165.

Kőszegi B, Szeidl A (2012) A model of focusing in economic choice. *Quart. J. Econom.* 128(1):53–104.

Lombardi M (2009) Reason-based choice correspondences. *Math. Social Sci.* 57(1):58–66.

Maltz A (2020) Exogenous endowment—Endogenous reference point. *Econom. J. (London)* 130(625):160–182.

Manzini P, Mariotti M (2012) Categorize then choose: Boundedly rational choice and welfare. *J. Eur. Econom. Assoc.* 10(5):1141–1165.

Masatlioglu Y, Nakajima D (2013) Choice by iterative search. *Theoret. Econom.* 8(3):701–728.

Ok EA, Ortoleva P, Riella G (2015) Revealed (p)reference theory. *Amer. Econom. Rev.* 105(1):299–321.

Palmeira MM (2010) The zero-comparison effect. *J. Consumer Res.* 38(1):16–26.

Scarpi D (2008) The impact of decoys and background information on consumers' preferences and decision making. *Internat. Rev. Retail Distribution Consumer Res.* 18(1):1–15.

Scholten M, Read D (2014) Better is worse, worse is better: Violations of dominance in intertemporal choice. *Decision (Washington DC)* 1(3):215–222.

Shafir E, Simonson I, Tversky A (1993) Reason based choice. *Cognition* 49(1–2):11–36.

Shampanier K, Mazar N, Ariely D (2007) Zero as a special price: The true value of free products. *Marketing Sci.* 26(6): 742–757.

Simonson I (1989) Choice based on reasons: The case of attraction and compromise effects. *J. Consumer Res.* 16(2):158–174.

Slovic P, MacPhillamy D (1974) Dimensional commensurability and cue utilization in comparative judgment. *Organ. Behav. Human Performance* 11(2):172–194.

Trueblood JS, Brown SD, Heathcote A, Busemeyer JR (2013) Not just for consumers: Context effects are fundamental to decision making. *Psych. Sci.* 24(6):901–908.

Tversky A (1972) Elimination by aspects: A theory of choice. *Psych. Rev.* 79(4):281–299.

Tversky A, Simonson I (1993) Context-dependent preferences. *Management Sci.* 39(10):1179–1189.

Wedell DH (1991) Distinguishing among models of contextually induced preference reversals. *J. Experiment. Psych. Learn. Memory Cognition* 17(4):767–778.

Zhang Y, Slovic P (2019) Much ado about nothing: The zero effect in life-saving decisions. *J. Behav. Decision Making* 32(1):30–37.