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Comparing Theories of Reference-Dependent Choice

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Preferences are influenced by the presence or absence of salient choice options, known as reference points. This behavioral tendency is traditionally attributed to the loss aversion and diminishing sensitivity assumptions of prospect theory. In contrast, some psychological research suggests that reference dependence is caused by attentional biases that increase the subjective weighting of the reference point's primary attributes. Although both theories are able to successfully account for behavioral findings involving reference dependence, this article shows that these theories make diverging choice predictions when available options are inferior to the reference point. It presents the results of 2 studies that use settings with inferior choice options to compare these 2 theories. The analysis involves quantitative fits to participant-level choice data, and the results indicate that most participants are better described by models with attentional bias than they are by models with loss aversion and diminishing sensitivity. These differences appear to be caused by violations of loss aversion and diminishing sensitivity in losses.

Keywords: multiattribute choice, reference dependence, endowment effect, prospect theory, attention

Reference dependence is one of the most studied phenomena in the domain of multiattribute preferential choice. According to research on reference dependence, salient choice options such as endowments, expectations, and aspirations affect a decision maker's preferences. Changing these reference points can reverse choices, subsequently violating choice consistency assumptions fundamental to theories of rational choice (Kahneman, Knetsch, & Thaler, 1991; Knetsch, 1989; Knetsch & Sinden, 1984; Samuelson & Zeckhauser, 1988; Thaler, 1980; Tversky & Kahneman, 1991). These violations have powerful implications for economic and consumer behavior, and, as a result, have received considerable attention from scholars of economics, marketing, and related fields (see, e.g., Hardie, Johnson, & Fader, 1993, and Kahneman, Knetsch, & Thaler, 1990). Reference dependence is also a robust feature of preferential choice. Subsequently, characterizing the cognitive mechanisms underlying reference dependence has become an important goal for psychologists interested in understanding human decision making (Ashby, Dickert, & Glöckner, 2012; Ashby, Walasek, & Glöckner, 2015; Bhatia, 2013; Carmon & Ariely, 2000; Herne, 1998; Johnson, Häubl, & Keinan, 2007; Trueblood, 2015; Tversky & Kahneman, 1991; Willemsen, Böckenholt, & Johnson, 2011).

Reference dependence is typically explained using multiattribute extensions of prospect theory (Köszegi & Rabin, 2006; Tversky & Kahneman, 1991). According to this account of reference dependence, decision makers process choice options in terms of gains and losses relative to the attribute values of the reference point. Additionally, decision makers are assumed to display a strong aversion to losses as well as diminishing sensitivity in both losses and gains. These assumptions provide an explanation for many of the reference-dependent choice behaviors observed thus far. These include the finding that reference points are often preferred over competing options (e.g., the endowment effect), and the finding that options that are clear improvements over the reference point and options that involve only small trade-offs from the reference point, are often chosen over options involving large trade-offs from reference point (Herne, 1998; Kahneman et al., 1991; Trueblood, 2015; Tversky & Kahneman, 1991).

Loss aversion and diminishing sensitivity are not, however, the only cognitive mechanisms capable of predicting reference-dependent choice. Recent work has argued that reference points alter the attention paid toward the attributes in the decision (Bhatia, 2013; Carmon & Ariely, 2000; Johnson et al., 2007; see also Birnbaum & Stegner, 1979, for a very similar early theory). Making a certain object a reference point increases attention toward the attributes associated with the object. This increases the weighting of these attributes, subsequently biasing choice.

By now, there is considerable process-level data supporting this mechanism. Memory and attention biases in favor of the attributes of endowments have been observed for choice options as diverse as sports tickets (Carmon & Ariely, 2000), mugs (Johnson et al., 2007) and consumer goods (Nayakankuppam & Mishra, 2005), using thought-listing (Johnson et al., 2007), mouse-tracking (Willemsen et al., 2011), eye-tracking (Ashby et al., 2015), recall (Nayakankuppam & Mishra, 2005), and a variety of other measures. Additionally, key reference point effects have been replicated in perceptual decision making, indicating that the mechanisms underlying reference dependence may be more general than loss aversion (which is fundamentally hedonic and typically applies only to preferential choice; Trueblood, 2015). Finally, Bhatia (2013) has provided a formal model of the attentional theory of reference dependence, and has shown that this model accurately

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predicts a wide range of observed reference-dependent behaviors, including those generally attributed to loss aversion.

So is reference dependence caused by attentional bias or by a combination of loss aversion and diminishing sensitivity? Although process-level data does support the attentional account, the choice predictions of these two theories have not yet been rigorously compared: Empirical work on this topic has examined only the settings in which the two theories make the same predictions, and this work has typically examined only qualitative choice patterns. Predicting choice accurately is the primary goal of any formal theory of decision making, and quantitatively comparing diverging choice predictions of attention and loss-aversion/diminishing-sensitivity can provide a rigorous test of the two theories of reference dependence.

This article attempts such a test. It presents the results of two studies with choice data for participants under the influence of reference points. These studies involve choices in settings in which attention and loss aversion/diminishing sensitivity theories make diverging predictions (as well as settings in which they make converging predictions). In order to compare the two theories, various specifications of the theories are applied to data on a participant level and evaluated in terms of their overall quantitative fit.

Reference-Dependent Choice

Traditional economic theories of behavior assume that decision makers' choices do not depend on salient but irrelevant options, such as their current endowments. Owning a particular option should not make that option more or less desirable compared with other options available to the decision maker. A very large number of behavioral experiments have shown this assumption to be incorrect. Endowing decision makers with a particular option, and making that option a reference point, increases the overall choice probability of that option, potentially generating preference reversals (Bateman, Munro, Rhodes, Starmer, & Sugden, 1997; Birnbaum & Stegner, 1979; Kahneman et al., 1990; Knetsch, 1989; Loewenstein & Adler, 1995; Samuelson & Zeckhauser, 1988; Tversky & Kahneman, 1991).

This result has been the focus of much empirical enquiry in psychology, economics, and marketing. Scholars of decision making in these fields have, by now, identified a series of systematic behaviors associated with reference dependence. These behaviors pertain to the effects of different types of reference points on binary forced choice, and serve as descriptive benchmarks for any formal theory of reference-dependent decision making.

In the standard reference-dependent choice task, the decision maker is given a choice between two options, $\boldsymbol{x}$ and $\boldsymbol{y}$. These options can be seen as being defined on a set of n attributes, and thus can be written in vector notation as $\boldsymbol{x} = (x_1, x_2, \ldots x_n)$ and $\boldsymbol{y} = (y_1, y_2, \ldots y_n)$. A reference point is some other salient option $\boldsymbol{r} = (r_1, r_2, \ldots r_n)$ that affects the choice between $\boldsymbol{x}$ and $\boldsymbol{y}$. For any choice options $\boldsymbol{x}$ and $\boldsymbol{y}$, and any reference point $\boldsymbol{r}$, we can write the probability of choosing $\boldsymbol{x}$ over $\boldsymbol{y}$ given $\boldsymbol{r}$ as $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r})$.

The best-known finding on reference dependence is the *endowment effect*. In the typical endowment effect experiment, participants are given a choice between two everyday items. Prior to this choice, they are told that they own one of the two items. These experiments typically find that the choice probability of an item is higher if decision makers are endowed with it compared with if they are not, and that altering the item that decision makers are endowed with often reverses the relative choice proportion of the two items. Thus, for example, Knetsch (1989) found that 89% of participants preferred a mug over a candy bar if they were initially endowed with the mug. In contrast, only 10% of participants preferred a mug over a candy bar if they were initially endowed with the candy bar. Related experiments find similar results with willingness-to-pay and willingness-to-accept measures (buying and selling prices) for endowed and nonendowed items.

This type of result also holds for nonendowed but salient options, such as past endowments, aspirations, endowments of others, objects in the immediate environment, and expected endowments (Bushong, King, Camerer, & Rangel, 2010; Clark & Oswald, 1996; Dhar & Simonson, 1992; Heath, Larrick, & Wu, 1999; Krajbich, Armel, & Rangel, 2010; Strahilevitz & Loewenstein, 1998). In all of these cases, making an option a reference point increases its choice probability. In a choice between two options $\boldsymbol{x}$ and $\boldsymbol{y}$, as in Figure 1, this implies that $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{x}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{y})$, that is, $\boldsymbol{x}$ is more likely to be chosen over $\boldsymbol{y}$ if it is the reference point compared with if $\boldsymbol{y}$ is the reference point.

A second finding is known as the *improvements versus trade-offs* effect (Herne, 1998; Tversky & Kahneman, 1991). This finding has been demonstrated using experiments in which different decision makers are endowed with different items, although, like the endowment effect, it also extends to reference points that are not actual endowments. In all of these settings, the improvements versus trade-offs effect refers to the increased preference for an option if it dominates the reference point (that is, if it is better than the reference point on at least one attribute and not worse than the reference point on every other attribute) compared with if the option involves trade-offs from the reference point. Thus, for example, in Tversky and Kahneman's (1991) study, 81% of participants initially endowed with a free dinner chose an option

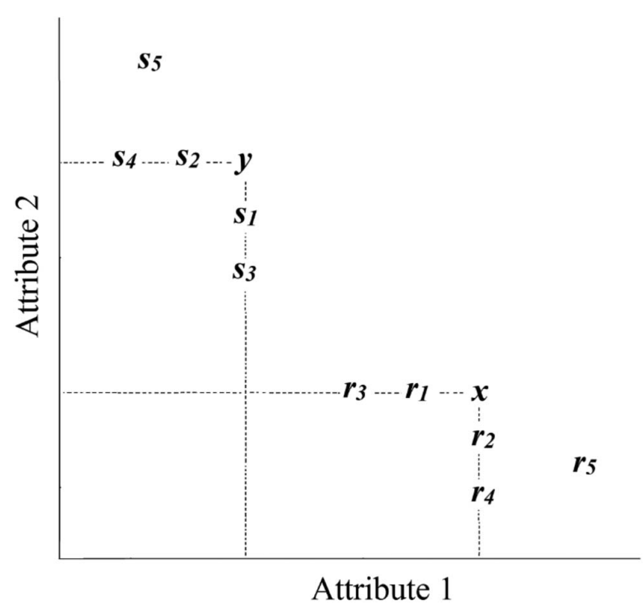

Figure 1. Reference-dependent anomalies in choice. Here, $\boldsymbol{x}$ and $\boldsymbol{y}$ represent choice alternatives, and $\boldsymbol{r}$ and $\boldsymbol{s}$ represent reference points.

offering two free dinners over an option offering a photo portrait and a calendar. In contrast, only 52% of participants chose this option if they were first endowed with a single calendar. In general, this effect emerges both when the reference point is dominated on its primary attribute (Tversky & Kahneman, 1991) and when it is dominated on its secondary attribute (Herne, 1998). In Figure 1, this implies that $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_1}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_1})$ and $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_2}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_2})$, respectively, that is, making the reference point $\boldsymbol{r_1}$ instead of $\boldsymbol{s_1}$ or $\boldsymbol{r_2}$ instead of $\boldsymbol{s_2}$ increases the choice probability of $\boldsymbol{x}$ over $\boldsymbol{y}$.

A related set of findings pertain to the extremity of the dominated reference point. Particularly, Herne (1998) finds that a reference point has a stronger effect on the choice probability of its dominating option if the reference point has a higher value on its primary attribute or if it has a lower value on its secondary attribute. Thus, increasing the relative amount of the reference point's primary attribute should increase the choice probability of the option dominating the reference point. In Figure 1, this implies that $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_1}) - P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_1}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_3}) - P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_3})$ and $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_4}) - P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_4}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_2}) - P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_2})$, that is, the improvement in the choice share of $\boldsymbol{x}$ over $\boldsymbol{y}$ is higher when the reference point switches from $\boldsymbol{s_1}$ to $\boldsymbol{r_1}$ and from $\boldsymbol{s_4}$ to $\boldsymbol{r_4}$, than when it switches from $\boldsymbol{s_3}$ to $\boldsymbol{r_3}$ or from $\boldsymbol{s_2}$ to $\boldsymbol{r_2}$, respectively.

A final finding is known as the *advantages and disadvantages* effect (Tversky & Kahneman, 1991). This, too, has been demonstrated using experiments in which different decision makers are endowed with different items, although, again, this effect extends to reference points that are not actual endowments. Overall, the advantages and disadvantages effect refers to the increased preference for an option if it involves small trade-offs from the reference point compared with if the option involves large trade-offs from the reference point. Thus, for example, in Tversky and Kahneman's (1991) experiment, 70% of participants preferred a job offering small amounts of social contact and a 20-min commute time over a job offering moderate social contact and a 60-min commute time, if they were first endowed with a job offering almost no social contact and a 10-min commute time. This choice share reduced to 33% if participants were endowed with a job offering a lot of social contact and an 80-min commute time. In Figure 1, the advantages and disadvantages effect implies that $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r_5}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{s_5})$, that is- making the reference point $\boldsymbol{r_5}$ instead of $\boldsymbol{s_5}$ increases the choice probability of $\boldsymbol{x}$ over $\boldsymbol{y}$.

It is valuable to note that the improvements versus trade-offs and advantages and disadvantages effects are very similar to the asymmetric dominance and compromise effects (Huber, Payne, & Puto, 1982; Simonson, 1989), which also involve divergent preferences based on dominance and trade-offs. Indeed, as outlined in the Discussion section, it is likely that both sets of findings stem from the same mechanism. That said, the improvements versus trade-offs and advantages and disadvantages effects involve a change in the reference point while keeping the composition of the choice set constant. Thus, participants in one condition may be endowed with an item dominated by $\boldsymbol{x}$, and participants in a second condition may be endowed with an item dominated by $\boldsymbol{y}$, but the choice is between $\boldsymbol{x}$ and $\boldsymbol{y}$ in both conditions. In contrast, the asymmetric dominance and compromise effects involve a change in the composition of the choice set without any change in the endowment. Thus, participants in one condition have to choose between $\boldsymbol{x}$, $\boldsymbol{y}$, and an item dominated by $\boldsymbol{x}$, whereas participants in another condition have to choose between $\boldsymbol{x}$, $\boldsymbol{y}$, and an item dominated by $\boldsymbol{y}$, but there are no changes to the endowments across conditions.

Theories of Reference Dependence

Loss Aversion and Diminishing Sensitivity

What are the psychological processes that generate these behaviors? Tversky and Kahneman (1991) argued that these behaviors can be explained using the key assumptions of prospect theory (see also Kahneman et al., 1990, 1991; Köszegi & Rabin, 2006; Thaler, 1980). According to Tversky and Kahneman, decision makers evaluate the available options not in terms of absolute amounts of each of the attributes in the options, but rather in terms of these amounts relative to the reference point. Additionally, losses are assumed to be more undesirable than corresponding gains are desirable (an assumption known as loss aversion), and both losses and gains are assumed to display diminishing sensitivity.

The prospect theory account of reference dependence is formalized using a utility maximization model. Utility models describe preferences for the various options using deterministic, static utility functions. For any options $\boldsymbol{x}$ and $\boldsymbol{y}$ and any reference point $\boldsymbol{r}$, we can write the utilities for $\boldsymbol{x}$ and $\boldsymbol{y}$ under the influence of $\boldsymbol{r}$ as $U(\boldsymbol{x}|\boldsymbol{r})$ and $U(\boldsymbol{y}|\boldsymbol{r})$. The probability of choosing $\boldsymbol{x}$ over $\boldsymbol{y}$ is typically given by a logistic transform of the difference in the utilities of $\boldsymbol{x}$ and $\boldsymbol{y}$. This is formalized as

$$P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{r}) = \frac{1}{1 + e^{-\gamma \cdot [U(\boldsymbol{x}|\boldsymbol{r}) - U(\boldsymbol{y}|\boldsymbol{r})]}} \tag{1}$$

In Equation 1, γ is a constant that determines the decision maker's sensitivity to the utility difference between $\boldsymbol{x}$ and $\boldsymbol{y}$. Large values of γ correspond to lower randomness in choice, and $\gamma = 0$ corresponds to perfectly random choice. For all $\gamma > 0$, $\boldsymbol{x}$ is more likely to be chosen over $\boldsymbol{y}$ whenever $U(\boldsymbol{x}|\boldsymbol{r}) > U(\boldsymbol{y}|\boldsymbol{r})$.

Overall, the utility for an option is assumed to be a simple sum of the option's attribute values (Köszegi & Rabin, 2006; Tversky & Kahneman, 1991). This implies that we can write $U(\boldsymbol{x}|\boldsymbol{r})$ as

$$U(\boldsymbol{x}|\boldsymbol{r}) = \textstyle\sum_{i=1}^{N} U_i(x_i|r_i) \tag{2}$$

Here, U_i are utility functions that apply the assumptions of loss aversion and diminishing sensitivity separately to each attribute. Although there are many ways to formalize these assumptions, the standard approach uses prospect theory's valuation function proposed by Tversky and Kahneman (1992). This is written as

$$U_i(x_i|r_i) = \begin{cases} (x_i - r_i)^{\alpha} & if\ x_i \geq r_i \\ -\lambda \cdot (r_i - x_i)^{\alpha} & if\ r_i > x_i \end{cases} \tag{3}$$

Prospect theory's value function assumes that loss aversion, specified by the parameter $\lambda > 1$, applies multiplicatively for losses. Additionally, diminishing sensitivity on both gains and losses is given by a power value function, specified by the parameter α: α is restricted to the interval (0, 1) to ensure diminishing sensitivity.

It is easy to see how this model is able to explain the endowment effect. With the assumption of loss aversion, negative deviations from a reference point hurt more than equivalent positive deviations are desirable. Thus, in Figure 1, if $\boldsymbol{x}$ is the reference point, staying with $\boldsymbol{x}$ does not lead to an increase or decrease in utility, and if $\boldsymbol{y}$ is the reference point, staying with $\boldsymbol{y}$ does not lead to an increase or decrease in utility. Moving from $\boldsymbol{x}$ to $\boldsymbol{y}$ or from $\boldsymbol{y}$ to $\boldsymbol{x}$ can, however, decrease utility because of loss aversion. This implies that it is more desirable to choose $\boldsymbol{x}$ over $\boldsymbol{y}$ when $\boldsymbol{x}$ is the reference point compared with when $\boldsymbol{y}$ is the reference point.

A similar logic can explain the improvements versus trade-offs effect and the advantages and disadvantages effect. With the additional assumption that both gains and losses display diminishing sensitivity, this theory can also explain the extremity-based moderators of the improvements versus trade-offs effect, which involves trading off gains and losses of different magnitudes.

Attentional Bias

A combination of loss aversion and diminishing sensitivity is not the only mechanism that can be at play in reference-dependent choice. As mentioned process-level data suggest that reference points determine the decision maker's attention toward attributes and, subsequently, the weights decision makers place on the attributes (Ashby et al., 2012, 2015; Carmon & Ariely, 2000; Johnson et al., 2007; Nayakankuppam & Mishra, 2005; Pachur & Scheibehenne, 2012; Willemsen et al., 2011). Changing reference points affects these attentional weights and can reverse choice.

Bhatia (2013) has specified an attentional theory of reference dependence within a sequential sampling model of preference accumulation. These types of models are frequently used to understand the psychological processes underlying preferential choice (Bhatia, 2014, in press; Bhatia & Mullett, 2016; Busemeyer & Townsend, 1993; Dai & Busemeyer, 2014; Krajbich et al., 2010; Roe, Busemeyer, & Townsend, 2001; Trueblood, Brown, & Heathcote, 2014; Tsetsos, Chater, & Usher, 2012; Usher & McClelland, 2004). They provide predictions regarding response times and confidence, and are also able to instantiate optimal speed–accuracy trade-offs for sequentially sampled information. Beyond this, sequential sampling and accumulation models provide a biologically and physiologically plausible perspective on decision making, and computations corresponding to sequential information accumulation have been observed in human and animal brains (see, e.g., Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Gold & Shadlen, 2007; Ratcliff & Smith, 2004).

According to Bhatia's (2013) model, reference points activate attributes based on their associations with these attributes. The association between an attribute and a reference point is assumed to be equal to the amount of the attribute in the reference point, and the attention probability of an attribute is assumed to be equal to the activation of the attribute compared with the activation of all other attributes. For an attribute i and a reference point $\boldsymbol{r}$, this attention probability is given by

$$\omega_i = \frac{\rho + r_i}{\sum_{k=1}^{n} \rho + r_k} \tag{4}$$

Here, ρ determines the overall baseline activation of the attributes, independent of the reference point. Note that as ρ increases, the relative effect of the reference point on attribute activation decreases. For very large values of ρ the reference point has almost no effect on choice. In this article, it is assumed that $\rho \geq 0$.

Once an attribute is attended to, it is evaluated and aggregated into the preferences for the available choice options. For a choice option $\boldsymbol{x}$, we can write the value functions that perform this evaluation as $V_i(x_i)$, which we assume are a given by a (reference-independent) power function. For parameter $\mu_{-} > 0$ this function is

$$V_i(x_i) = x_i^{\mu} \tag{5}$$

In Bhatia's (2013) model, the decision maker is assumed to attend to each attribute sequentially. Changing reference points can alter choice by affecting attention probabilities. In order to facilitate model fitting, we will simplify Bhatia's sequential sampling assumption while nonetheless allowing for reference points to affect attribute attention. In particular, we will assume that the dynamics of the preference accumulation process are specified by a basic form of decision field theory (Busemeyer & Townsend, 1993; also see Bhatia, 2014, and Rieskamp, 2008). According to this simplification, the change in relative preference at any given time is normally distributed with mean $\delta = \delta_x - \delta_y$ and variance $\sigma^2 = \sigma_x^2 + \sigma_y^2 - 2 \cdot \sigma_{xy}$. Here, δ_x is the expected sampling value for $\boldsymbol{x}$, given by $\delta_x = \sum_{i=1}^{n} \omega_i \cdot V_i(x_i)$, and σ_x^2 is the variance of the sampling value of $\boldsymbol{x}$, given by $\sigma_x^2 = \sum_{i=1}^{n} \omega_i \cdot [V_i(x_i) - \delta_x]^2$; δ_y and σ_y^2 are similarity defined, and σ_{xy} is the sampling covariance of the values of $\boldsymbol{x}$ and $\boldsymbol{y}$, given by $\sigma_{xy} = \sum_{i=1}^{n} \omega_i \cdot [V_i(x_i) - \delta_x] \cdot [V_i(y_i) - \delta_y]$.

Decision makers are assumed to use a single accumulator to aggregate relative preferences to a positive threshold θ or a negative threshold $-\theta$. If θ is crossed, then the decision maker selects $\boldsymbol{x}$, and if $-\theta$ is crossed, the decision maker selects $\boldsymbol{y}$. As in prior experimental tests of decision field theory (such as Rieskamp, 2008), we assume that θ corresponds to θ^*/σ of the original decision field theory model. With this structure, the overall choice probability of $\boldsymbol{x}$ over $\boldsymbol{y}$ given a reference point $\boldsymbol{r}$ is

$$\mathrm{P}(\boldsymbol{x}, \boldsymbol{y} | \boldsymbol{r}) = \frac{1}{1 + e^{-\frac{2 \cdot \delta \cdot \theta}{\sigma}}} \tag{6}$$

Equation 6 is highly similar to Equation 1, and if we restricted $\sigma = 2$ we would obtain a utility based representation for the attentional model, that is passed through a logistic transform to determine choice. This alternate specification of the attentional model will not be studied in this article, as it lacks psychological rationale and additionally shares its modal choice predictions with the specification described by Equation 6.

Note that the mathematical structure outlined here highlights some of the key differences between the two theories. The major difference is with loss aversion: The attentional theory does not distinguish between gains and losses, and thus does not (explicitly) emphasize losses more than gains. For this reason, the attentional theory also does not impose diminishing sensitivity in both losses and gains. The curvature of the value function is largely identical (either concave, reflecting diminishing sensitivity, or convex, reflecting increasing sensitivity) for all attribute amounts, independent of the reference point. Instead of loss aversion and diminishing sensitivity in losses and gains, the attentional theory assumes biased attention, which overweighs or underweighs the attributes, depending on the reference point.

It is easy to see how biased attention can explain the endowment effect. As attribute attention probabilities are increasing in the amounts of the attributes in the reference point, attributes that are highly present in the reference point are most likely to be attended to. These are the attributes that are then accumulated into preferences. Subsequently, choice options that are particularly desirable on these attribute are more likely to be selected. Thus, in Figure 1, if $\boldsymbol{x}$ is the reference point, the decision maker is more likely to attend to Attribute 1 compared with when $\boldsymbol{y}$ is the reference point. This means that ω_1, and, subsequently, $\delta = \delta_x - \delta_y$, is higher when $\boldsymbol{x}$ is the reference point. Because of this we obtain $P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{x}) > P(\boldsymbol{x}, \boldsymbol{y}|\boldsymbol{y})$. The same logic can explain the improvement versus trade-offs effect, its dependence on reference point extremity, and the advantages and disadvantages effect. Overall, any reference point in Figure 1 that has been shown to bias preferences in favor of $\boldsymbol{x}$ is also strongest on $\boldsymbol{x}$'s primary attribute.

The endowment effect, the improvement versus trade-offs effect, and the advantages and disadvantages effect have all been documented in perceptual choice (Trueblood, 2015). Attention (unlike loss aversion) is a domain-general nonhedonic psychological mechanism, and Bhatia's (2013) model can be used explain both the preferential and the perceptual instantiations of these effects. Additionally, one unique benefit of sequential sampling and accumulation models compared with their static utility counterparts pertains to their ability to predict the relationship of choice with decision time. Bhatia has shown that the attentional model can explain the increase in the strength of the endowment effect with decision time, observed by Ashby et al. (2012). This article, however, will not be examining decision times.

Finally, note that there are a number of distinct attentional theories of reference dependence that vary in subtle ways. This article uses Bhatia's (2013) model for the tests, as it makes explicit the property shared by all existing attentional theories (that attention is increasing in the reference point's attribute amounts, for desirable attributes), and is, in addition, the only quantitative model of attention-based reference dependence proposed thus far. All of the tests reported in this article can be repeated with alternate attentional theories (such as those of Carmon & Ariely, 2000, or Johnson et al., 2007) once these theories are specified within a suitable mathematical framework (also see Birnbaum & Stegner, 1979, for a related mathematical model involving buying and selling price judgments instead of choice).

Model Fitting

In our fits, we will consider both the simplified models which assume identical parameters across attributes, as well as extended versions of these models, which assume that the parameters differ across attributes. As we will be examining settings with only two attributes, these extended models will have five parameters each (α_1, λ_1, α_2, λ_2, and γ for loss aversion/diminishing sensitivity, or μ_1, ρ_1, μ_2, ρ_2, and θ for attention) compared with three parameters in their simplified counterparts (α, λ, and γ, or μ, ρ, and θ). For this reason, the extended models will be referred to as LA5 and AT5 and the simplified models will be referred to as LA3 and AT3.

Note that we assume that LA3 and LA5 have the same diminishing sensitivity for gains and losses. This is in contrast to the original Tversky and Kahneman (1991, 1992) model, which allows diminishing sensitivity to vary for gains and losses. Recent work suggests that flexibility in this parameter comes at the cost of model overspecification and parameter interaction (Nilsson, Rieskamp, & Wagenmakers, 2011), as the effects of loss aversion can also be captured by the diminishing sensitivity parameter if it is allowed to vary for gains and losses. A similar concern explains why we do not permit explicit attribute weights for LA5. This model already allows varying utility functions for the two attributes (in the form of separate diminishing sensitivity and loss aversion parameters), and adding an additional weighting parameter to such a model may lead to parameter interactions.

Nonetheless, the Appendix considers extensions of LA3 and LA5, which allow the diminishing sensitivity parameter to vary across losses and gains, and for the two attributes to have different weights. The use of these extended models does not alter any of the key results in this article. For this reason, the main text will limit its analysis to LA3 and LA5. This also facilitates intuitive model comparisons, as LA3 and LA5 have the same number of parameters, and the same parametric structure, as AT3 and AT5.

The Appendix also presents simplifications of LA3 and LA5, which either avoid the assumption of diminishing sensitivity (assuming, instead, a linear value function) or avoid the assumption of loss aversion (assuming, instead, that gains are valued as much as losses). Of course, these simplifications imply that these models are unable to account for the findings that loss aversion/diminishing sensitivity was initially formulated to explain (see Figure 1). Nonetheless, they are useful for examine the ways in which the assumptions of this theory are violated.

All models will be fit by maximizing log-likelihood performed using the simplex routine, as implemented in MATLAB. As this routine can display sensitivity to the starting points used in its iterated search process, we will run this routine 10,000 times for each model fit, selecting starting points from a grid of parameter values. We will use the interval (0, 1) for the starting points for the diminishing sensitivity parameter, α, the value function parameter, μ, and the attribute activation parameter, ρ. We will also use the interval (0, 10) for the starting points for the choice sensitivity parameter, γ, and the threshold parameter, θ. Finally, we will consider the interval (1, 10) for the starting points of the loss aversion parameter, λ. These ranges have been previously used for fitting prospect theory's utility function in risky choice (Glöckner & Pachur, 2012; Nilsson et al., 2011; Rieskamp, 2008), and also provide feasible parameter values for the attribute activation function.

As mentioned in the model introductions, we will apply constraints to the diminishing sensitivity parameter ($1 > \alpha > 0$) and the loss aversion parameter ($\lambda > 1$). This is because these parameter ranges are necessary to generate diminishing sensitivity and loss aversion, two fundamental assumptions of prospect theory. Without these restrictions, the prospect theory-based models would be unable to predict existing behavioral effects (of course that the simplifications to LA3 and LA5 fit in the Appendix do not impose these restrictions). We will also restrict the attribute activation parameter, $\rho > 0$, and power value parameter, $\mu > 0$, in order to ensure that attribute attention probabilities and attribute values are well-defined. Additionally, the model fits will apply this approach to all the choices obtained from the participants, and will not explicitly consider order effects in choice. This is a useful simplification, one which should not affect the relative fits between the model.

It will often be useful to examine the strength of the differences in model fit. For this we will utilize the Bayesian information criterion (BIC), which asymptotically approximates a transformation of the Bayesian posterior probability of the candidate model. In certain settings, comparing two models using the BIC is equivalent to model selection based on Bayes factor. The BIC value for a particular model fit on a dataset is specified by

$$\mathrm{BIC} = -2 \cdot L + \ln(m) \cdot k \tag{7}$$

Here, L is the best fit log-likelihood of the model in consideration, m is the number of data points, and k is the number of flexible parameters in the model. Models with lower BIC values are considered to have better fit.

Diverging Predictions

Before proceeding, let us consider the differences between the two theories of reference dependence. This is necessary to establish both whether these two theories are distinguishable, as well as the type of data we would need to perform an appropriate test of the theories.

The reference-dependent behavioral findings all involve choice options that are as desirable as, or superior to, the reference point (see Figure 1), and the two theories make similar qualitative predictions for these types of reference points. In contrast, these theories diverge when the available options are inferior to the reference point. Consider, for example, the left and right panels of Figure 2. These present the relative choice probabilities for an option $\boldsymbol{x} = (1, 0)$ compared with an option $\boldsymbol{y} = (0, 1)$ under the influence of different reference points $\boldsymbol{r}$, for the simplified loss aversion/diminishing sensitivity and attention models of reference dependence (LA3 and AT3), respectively. These figures have set $\alpha = .5$, $\lambda = 2$, and $\gamma = 1$ for LA3, and $\rho = \mu = \theta = 1$ for AT3. Each location in each figure indicates the choice probability of $\boldsymbol{x}$ over $\boldsymbol{y}$ in the presence of a reference point positioned at that location. Higher choice probabilities for $\boldsymbol{x}$ are indicated by darker shades on the grids. Note that in the right panel (corresponding to the attentional model), the preferences for $\boldsymbol{x}$ are always higher when $\boldsymbol{r}$ is stronger on Attribute 1, and preferences for $\boldsymbol{y}$ are always higher when $\boldsymbol{r}$ is stronger on Attribute 2. This does not, however, hold for the left panel (corresponding to the loss aversion/diminishing sensitivity model), in which increases to $\boldsymbol{r}$ on Attribute 1 can reduce the preference for $\boldsymbol{x}$ when $\boldsymbol{x}$ is inferior to $\boldsymbol{r}$, and increases to $\boldsymbol{r}$ on Attribute 2 can reduce the preference for $\boldsymbol{y}$, when $\boldsymbol{y}$ is inferior to $\boldsymbol{r}$. For this reason, the panels differ qualitatively for values of $\boldsymbol{r}$ that are in the top two quadrants or in the bottom right quadrant, that is, when at least one choice option is inferior to the reference point. In contrast, these panels look nearly identical in the bottom left quadrant, in which the choice options are superior to the reference point.

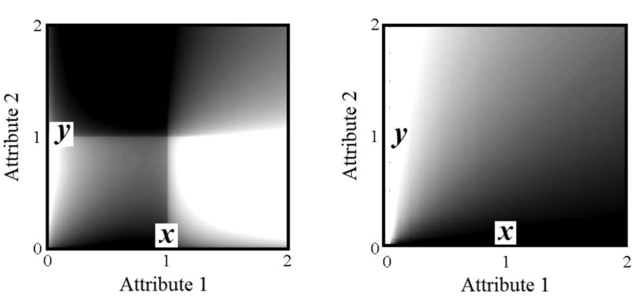

Figure 2. Choice probabilities for $\boldsymbol{x}$ over $\boldsymbol{y}$ for varying reference points as predicted by loss-aversion/diminishing-sensitivity models of reference dependence (left panel) and attentional models of reference dependence (right panel). Darker shades indicate higher choice probabilities for $\boldsymbol{x}$ over $\boldsymbol{y}$.

Ultimately, the attention theory of reference dependence always predicts an increase in the preference for an option when the relative amount of that option's strongest attribute is higher in the reference point. This occurs because higher amounts of an attribute in the reference point lead to higher activation of this attribute, subsequently giving it a larger attention probability and more influence in the preference accumulation process. In contrast, the loss aversion/diminishing sensitivity theory can predict a reduction in the preference for an option when the relative amount of that option's strongest attribute is increased in the reference point. If the option is inferior to the reference point, such an increase can result in higher perceived losses for the option, which, because of the combination of loss aversion and diminishing sensitivity, make the option appear less desirable than its competitor.

The divergence outlined here holds even with more flexible variants of the two theories. It is largely robust to differences in specific functional instantiations of loss aversion and diminishing sensitivity or specific attribute activation and value functions. These insights are valid, however, only for the parameters that generate both loss aversion and diminishing sensitivity. Of course, these parameter values are also required to accommodate the empirical findings discussed earlier in this article.

Study 1

The fact that the loss aversion/diminishing sensitivity and attentional theories of reference dependence diverge when the available options are inferior to the reference point suggests that settings with inferior choice options can be used to compare the two theories. Study 1 attempts such a comparison using quantitative participant-level model fits.

Method

Participants. Seventy-six students from an American university took part in the experiment (44% male; M age = 22.89 years, SD age = 5.90), which was conducted in a behavioral laboratory on the university campus. The participants were compensated with course credit. Additionally, as an incentive, they were also given one of the choice options they selected in the experiment (a combination of Reese's Pieces and Kit Kat candy bars). The study received ethics committee approval.

Materials and design. Study 1 was designed to perform a within-participant analysis of reference dependence. Note that it is difficult to give a single participant different reference points for the same set of options over the course of an experiment. Thus, the experiment in Study 1 gave all participants only one reference point and then asked them to make a number of different choices under the influence of this reference point.

Choice options and reference points were defined on two dimensions: Kit Kat and Reese's Pieces, two popular but distinct types of chocolates. Only one reference point was used in this experiment, and this was three Kit Kats and three Reese's Pieces. There were 120 different binary choices, with each choice option in each choice problem containing different combinations of Kit Kats and Reese's Pieces. For example, one of the choices offered participants "2 Kit Kats and 2 Reese's Pieces" or "4 Kit Kats and 0 Reese's Pieces."

Choice problems were generated by selecting the number of Kit Kats and the number of Reese's Pieces randomly and uniformly from the interval [0, 6] for each choice option, and removing choice problems in which one option had more of both types of chocolate than the other, or in which choice options differed by a total of more than three chocolates. Overall, half of the choice problems used in the experiment involved options that were relatively inferior to the reference point. As discussed, the attentional and loss aversion/diminishing sensitivity theories of reference dependence make diverging predictions with inferior choice options, implying that the choices used in Study 1 permit a strong quantitative test of the two theories.

Note that the choices in this experiment can be described using the notation introduced earlier in this article. Particularly, the reference point can be written as $\boldsymbol{r} = (3, 3)$, and different choice options can be written as $\boldsymbol{x} = (x_1, x_2)$ and $\boldsymbol{y} = (y_1, y_2)$, with x_1 and y_1 corresponding to the amount of Kit Kats in the two options and x_2 and y_2 corresponding to the amount of Reese's Pieces in the two options. The various attentional and loss aversion/diminishing sensitivity models can subsequently be fit on the data obtained in this experiment, with the techniques specified in Equations 1 to 6.

Procedure. Participants were endowed with the reference point, three Kit Kats and three Reese's Pieces, at the start of the experiment. This was done by placing the chocolates in front of each participant. The participants were told that the chocolates were theirs (as additional compensation for taking part in the experiment), but that they may be taken away at the end of the experiment. Participants then performed a filler task. After the filler task, they were asked to answer the 120 choice questions. They were told that after answering the questions, a coin would be flipped. If the coin landed heads they would get their endowment (three Kit Kats and three Reese's Pieces), but if the coin landed tails, they would not receive this endowment. Instead, one of the 120 choice questions they answered would be randomly selected and their choice in this question would be given to them. This design allowed us to obtain multiple incentivized choices from individual participants. All experimental tasks were performed on a computer interface in private cubicles, with no visual access to other participants. Finally, the reference point (three Kit Kats and three Reese's Pieces) was kept in front of the participants as they made the 120 choices, ensuring that the reference point remained salient throughout the experiment.

Results

Choice proportions. Seventy-six participants answered 120 choice problems in this experiment, generating a total of 9,120 choices. Before examining quantitative model fits to these choices (the primary goal of this article), we can first qualitatively examine the general patterns in these choices. Overall, participants should display a preference for choice options that have a higher total number of chocolates. Similarly, we would also expect participants to prefer choice options consisting of roughly equal amounts of the two chocolates, over options with a high dispersion in the two types of chocolates (large amounts of one type of chocolate but small amounts of the other). We might also expect participants to display a preference for one of the two types of chocolates over the other.

These hypotheses were tested with a single logistic regression on the entire data. The dependent variable was the choice of the left option, and the independent variables captured the difference in the total amount of chocolates in the left option relative to the right option, the difference in dispersion in the left option relative to the right option, and whether the left option had more Kit Kats or more Reese's Pieces relative to right option. The dispersion of an option was formalized as the absolute value of the difference between the number of Kit Kats and the number of Reese's Pieces in that option. The analysis controlled for participant heterogeneity by allowing for participant-level random intercepts in the logistic regression.

As expected, the regression revealed a preference for options with a higher total number of chocolates ($\beta = 0.36$, $z = 20.77$, $p < .01$) and a preference for options with a lower dispersion ($\beta = -0.07$, $z = -9.43$, $p < .01$). Additionally, participants displayed an overall preference for choice options that have more Kit Kats compared with Reese's Pieces ($\beta = 0.45$, $z = 20.13$, $p < .01$). Finally, as expected, participants did not have a preference for options displayed on the left or right side of the screen ($p > 0.10$).

The analysis also examined whether being superior or inferior to the reference point has a qualitative effect on the likelihood of a choice option being selected. This was done by separating the data set into two subsets, the first involving choices between options that dominate the reference point (have more of both types of chocolates than the reference point) and options that do not dominate the reference point, and the second involving choices between options that are dominated by the reference point (have less of both types of chocolates than the reference point) and options that are not dominated by the reference point. Two logistic regressions, testing whether a dominating option was more likely to be selected in the first set, and whether a dominated option was less likely to be selected in the second set, were then run. The regressions controlled for the difference in the total number of chocolates in the dominating/dominated option relative to the competitor, the dispersion of the dominating/dominated option relative to the competitor, and whether the dominating/dominated option had more Kit Kats. These regressions also included participant-level random intercepts. Consistent with the earlier analysis, both regressions found that dominating/dominated options with more total chocolates, less dispersion, and more Kit Kats than the competitor are significantly more likely to be chosen ($p < 0.05$ for all coefficients). There was not, however, any significant effect of being dominating or being dominated ($p > 0.10$). This suggests that the rankings of attribute values of available options, relative to the reference point, may not play a role in determining choice. Note that loss aversion/diminishing sensitivity models do assume changes in preferences based on ordinal comparisons with the reference point, suggesting that these types of models may not be able to provide a good fit to the data.

Model fits. We can more rigorously test the models by fitting them to choice data, using the techniques specified in the previous section. For this analysis, each of the four models were fit separately for each participant, by finding the participant-level parameters that maximized the log-likelihood of the model for the participant.

Using the BIC to compare the model performances of the simplified models, 72% of participants were better fit by AT3, whereas 28% were better fit by LA3. Similar differences were obtained between the extended models, with 83% of participants being better fit by AT5, and 17% being better fit by LA5. Overall, the best-performing of the four models was AT5, which had the lowest median BIC value and also provided the best BIC-based fit to 79% of the participants. Model performance is summarized in Table 1. The Appendix presents model performance for extensions and simplifications of LA3 and LA5, and shows that relative fits are largely unchanged.

This paper also examined the predictions for each of the models for each participant in each choice problem and compared these predictions with the actual choices of the participant. The predictions are considered to be accurate if they predict the participant's actual choice with a probability higher than 0.5 (that is if the modal choice prediction matches the participant's actual choice). It found that the participant-level fits for the AT3 model could accurately predict 60% of all choices, whereas the fits for the LA3 model could accurately predict 62% of all choices. This did not reach statistical significance when evaluated with a logistic regression ($p > .05$). For the extended models, participant-level fits for AT5 were able to accurately predict 91% of all choices, and fits for LA5 were able to accurately predict 84% of all choices, which is a statistically significant difference ($\beta = 0.84$, $z = 17.33$, $p < .01$). AT5 is the best-performing model according to the BIC, and these tests show that it is also able to give a good overall account of the choice data. This is displayed in Figure 3, which plots the aggregated choice probability for the left option in each of the 120 choices, against the aggregated predicted choice probability for the left option obtained using participant-level fits for AT5.

Parameters. To understand why the attentional models outperform the loss aversion/diminishing sensitivity models, this paper examined the best-fitting parameter values. These parameters are displayed in Table 1. As can be seen in this table, the AT3 and AT5 models do seem to have reasonable values for their parameters: All of these parameters are well above their lower bound of zero. Additionally, although the baseline activation parameters for AT5 are fairly high, so is the threshold parameter (which offsets the impact of high levels of baseline activation).

Table 1
Model Fits for Study 1

Model	α_1	λ_1	α_2	λ_2	γ	Best	BIC
LA3	.75 [32%]	1.10 [48%]	—	—	.27	9%	174.96
LA5	1.00 [59%]	2.27 [32%]	.87 [46%]	1.13 [45%]	1.35	8%	85.24
	μ_1	ρ_1	μ_2	ρ_2	θ	Best	BIC
AT3	.60	.91	—	—	.80	4%	173.71
AT5	.94	60.34	.61	77.57	3.76	79%	68.05

Note. The parameter values correspond to the median parameters from the fits. "Best" refers to the proportion of participants for which the model provides the strongest fit according to the BIC. "BIC" refers to the median BIC values from the best-fitting models. The figures in the squared brackets below the parameters of LA3 and LA5 refer to the proportion of participants with weak levels of diminishing sensitivity or loss aversion ($\alpha > .99$ or $\lambda < 1.01$, respectively). Attribute 1 corresponds to Kit Kats and Attribute 2 corresponds to Reese's Pieces. Finally, the parameter values are rounded, which is why $\alpha_1 = 1.00$ for LA5 (the true median value of this parameter is .9998). BIC = Bayesian information criterion.

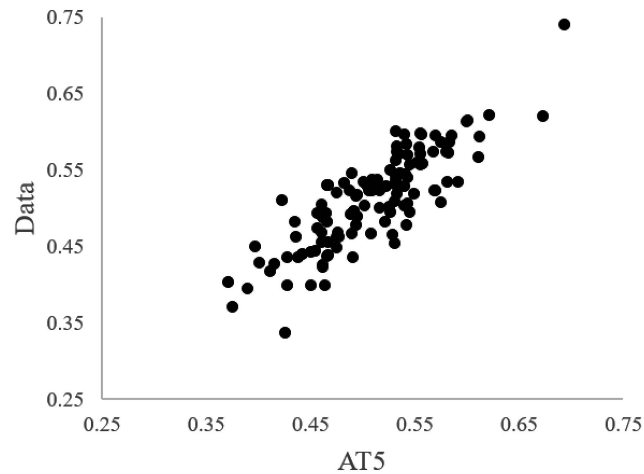

Figure 3. A plot of the aggregated choice probability for the left option in each of the 120 choices in Study 1, as predicted by participant-level fits for AT5 (the best-performing model according to BIC).

In contrast to the attentional models, the LA3 and LA5 models often display weak diminishing sensitivity and loss aversion. In fact, 32% of participants had a diminishing sensitivity parameter $\alpha > .99$, and 48% had a loss aversion parameter $\lambda < 1.01$ for LA3. Likewise, 59% of participants had $\alpha > .99$ for Kit Kat, 46% had $\alpha > .99$ for Reese's Pieces, 32% of participants had $\lambda < 1.01$ for Kit Kat, and 45% had $\lambda < 1.01$ for Reese's Pieces. Overall, 78% of participants had either $\alpha > .99$ or $\lambda < 1.01$ for LA3, and 95% of participants had either $\alpha > .99$ or $\lambda < 1.01$ for at least one of the attributes in LA5. Median parameter values also reflect these patterns. As shown in Table 1, the median value of λ for LA3 is 1.10, and the median value of λ for Reese's Pieces is only 1.13 for LA5. Both of these indicate fairly weak loss aversion. Likewise, the median value of α for Kit Kat exceeds 0.99, indicating very weak diminishing sensitivity. The Appendix displays model fits for variants of LA3 and LA5 without the assumptions of diminishing sensitivity and loss aversion, and consistent with the findings outlined here, shows that these simplified models often outperform LA3 and LA5.

It is possible that the participants with especially weak diminishing sensitivity or loss aversion were also the ones best described by attentional reference dependence. This paper tested this and found that our intuition was confirmed. Overall, of the 17 participants that displayed reasonable diminishing sensitivity and loss aversion for LA3, only 35% were better fit by AT3 compared with LA3. For the remaining 59 participants who had weak diminishing sensitivity or loss aversion for LA3, 83% were better fit by AT3 compared with LA3. The median difference in the BIC scores for LA3 relative to AT3 is −0.01 for the first group compared with 0.60 for the second group. These differences were statistically significant when examined with a linear regression ($\beta = 5.13$, $z = 3.06$, $p < .01$).

Likewise, of the four participants that had reasonable diminishing sensitivity and loss aversion for both attributes for LA5, only 25% were better fit by AT3 compared with LA3. For the remaining 72 participants who had weak diminishing sensitivity or loss aversion for at least one attribute, 86% were better fit by AT3 compared with LA3. The median differences in the BIC scores for LA5 compared with AT5 were −4.28 for the first group, compared with 19.75 for the second group. These differences were also statistically significant when examined with a linear regression ($\beta = 22.21$, $z = 2.67$, $p < .01$).

If we did not constrain the parameter ranges for LA3 and LA5, it is likely that we would observe $\alpha > 1$ (indicating increasing sensitivity) or $\lambda < 1$ (indicating loss seeking) for many participants. This suggests that the key assumptions of the loss aversion/diminishing sensitivity models may be frequently violated for the choice problems considered in this experiment—choice problems in which choice options are often inferior to the reference point.

Discussion

Study 1 compared the attention and loss aversion/diminishing sensitivity theories of reference dependence on a participant level. It used a single reference point and gave each participant multiple choices for options both inferior to and superior to this reference point. A qualitative analysis of choice proportions did not reveal any preference for options dominating the reference point or aversion toward options being dominated by the reference point. Models based on loss aversion involve ordinal comparisons with the reference point, indicating that these models may not be able to describe participant behavior in this experiment.

This intuition was confirmed by formal model fitting. Overall, this paper found that the majority of participants were better fit by the attention models compared with the corresponding loss aversion/diminishing sensitivity models, using the BIC as the criterion. The best-performing model of all four examined models was AT5, which had the best BIC score for 79% of the participants. Additionally, the best-fit diminishing sensitivity parameters and loss aversion parameters for LA3 and LA5 were frequently very close to 1, indicating that many participants may have had increasing sensitivity or may have been loss seeking. Indeed, participants with very weak levels of diminishing sensitivity and loss aversion were typically the ones that were better fit by the attentional models. It would be possible to improve the fit of the LA3 and LA5 models by not constraining their parameters; however, such models would then be unable to explain the existing behavioral findings associated with reference dependence (which rely on both loss aversion and diminishing sensitivity).

Study 2

Study 1 examined reference dependence on an individual level. In order to do so, it gave participants binary choices under the influence of a single reference point. This design is useful for studying preferences for options that are superior to and inferior to the reference point, and thus for comparing the attentional and loss aversion/diminishing sensitivity theories of reference dependence. However, it does not involve a varying reference point, and thus cannot be used to study how preferences change as a function of the reference point.

Study 2 attempts to address this problem. It involves the use of two different reference points, which contain different combinations of the attributes in consideration. Although every participant is given a single reference point, the specific reference point that each participant is exposed to is determined randomly. All participants, regardless of the reference point used, make the same set of binary choices. Study 2 also involves two other changes relative to Study 1. First, in order to improve its ability to discriminate between the two theories, Study 2 uses only choice options that are inferior to the reference points (as discussed attentional and loss aversion/diminishing sensitivity theories make divergent predictions for these types of choices). Second, in order to verify whether attention is in fact at play in the decision, Study 2 uses a mouse-tracking interface, which is able to record how decision makers attend to the various attributes when deliberating between the choice options.

Method

Participants. Seventy-two students took part in the experiment (52% male; *M* age = 21.59 years, *SD* age = 4.09), which was conducted in a behavioral laboratory at a British university. The participants were compensated with money.

Materials and design. The choice options used in this experiment were hypothetical vacations in Spain. Each vacation was defined on two dimensions: nights in Ibiza (an island with a vibrant nightlife) and nights in Barcelona (a city known for its cultural and artistic attractions). Participants were given either "6 nights in Barcelona" or "6 nights in Ibiza" as their reference point, and, after being exposed to their reference point and some filler questions, made 83 different choices between vacations that involved different combinations of nights in Barcelona and nights in Ibiza. For example, one of the choice problems used offered participants the choice between "2 nights in Ibiza and 4 nights in Barcelona" and "5 nights in Ibiza and 2 nights in Barcelona." Seventy-eight of the choice problems used were taken from Study 1. These choice problems involved all vacation combinations that differed by, at most, one total vacation day. An additional five choice problems were added to this list. These involved the choice between "*k* nights in Ibiza and 0 nights in Barcelona" and "0 nights in Ibiza and *k* nights in Barcelona," where *k* was an integer between 1 and 5. Changes in choices across these problems can be used to test the influence of the reference point.

Unlike Study 1, Study 2 used a MouseLAB interface (Willemsen & Johnson, 2011) in order to study the attentional biases predicted by the attentional theory of reference dependence. This involved the presentation of the reference point and the two options in table format, with three rows, corresponding to the reference point, and the two choice options, and two columns, corresponding to the number of nights in each of the two locations that the choice options offered. The cells corresponding to the attribute values of the reference point were uncovered, but those corresponding to the attribute values of the choice options were obscured by gray boxes. Participants had to click on individual gray boxes in order to determine the number nights the corresponding vacation offered in the corresponding location. Biases in attribute attention can be examined by recording the number of times participants clicked on the attributes, as well as the total time spent looking at these attributes. An example of this interface is displayed in Figure 4. Note that the order in which the attributes were presented (i.e., whether the reference point's primary attribute was in the left column or right column) was randomized across participants.

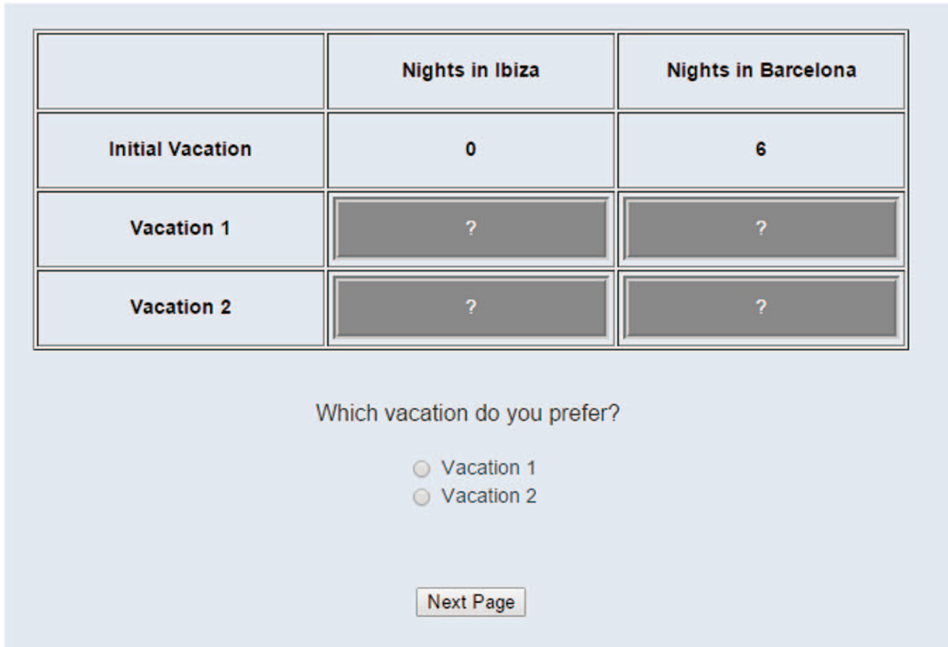

Figure 4. Example of MouseLAB interface used in Study 2. Here, the participant is endowed with 6 nights in Barcelona. Attribute values obscured by the gray boxes can be uncovered by clicking on these boxes. At any time, only one box can be opened. See the online article for the color version of this figure.

Again, the choices in this experiment can be described using the notation introduced earlier in this article. Particularly, the reference points can be written as $\boldsymbol{r} = (6, 0)$ or $\boldsymbol{r} = (0, 6)$, and different choice options can be written as $\boldsymbol{x} = (x_1, x_2)$ and $\boldsymbol{y} = (y_1, y_2)$, with x_1 and y_1 corresponding to nights in Barcelona, and x_2 and y_2 corresponding to nights in Ibiza. The various attentional and loss aversion/diminishing sensitivity models can subsequently be fit on the data obtained in this experiment, with the techniques specified in Equations 1 to 6.

Procedure. Participants were told to imagine that they had won a free vacation to Spain. This vacation consisted of 6 nights in Barcelona (if they were endowed with the first reference point) or 6 nights in Ibiza (if they were endowed with the second reference point). After a filler task, the participants were then told that the vacation was unavailable and that they instead had to choose between pairs of other vacation options. They were then introduced to the MouseLAB presentation format. After they were comfortable with this format, they made the 83 choices in the experiment. All experimental tasks were performed on a computer interface in private cubicles, with no visual access to other participants. As can be seen in Figure 4, each choice problem displayed the reference point at the top, ensuring that the reference point was salient throughout the experiment.

Results

Choice proportions. As in previous studies, we can begin by examining the general patterns in choices. Note that there were 5,976 total choices in this experiment, and we have attention data for each of these decisions. In 254 of these choices, participants did not click on any of the boxes before submitting their choices, indicating that they did not have any attribute-level information on which to base their decisions. These 254 observations are excluded in all subsequent analysis. Also note that there was a decrease in click counts as trials progressed. However, this is largely because of the first few trials (in which participants clicked a lot). The effect of trial number on click count disappeared after 10 trials. The subsequent analysis considers all trials, though the results do not change if we remove the first 10 trials from the analysis.

Using a logistic regression with participant-level random intercepts, this paper found that decision makers were more likely to choose choice options with more total vacation days ($\beta = 0.74$, $z = 18.34$, $p < .01$), lower dispersion ($\beta = -0.17$, $z = -16.13$, $p < .01$), and fewer nights in Ibiza ($\beta = -0.34$, $z = -12.50$, $p < .01$).

We can also use the data from this experiment to test for the effects of the reference points. As this experiment involves choices between inferior options, the reference point is never offered to the participants as a choice, and thus we cannot directly test for the standard endowment effect. However, we can examine whether the choice frequencies for the various options vary based on whether the participant was initially given 6 nights in Barcelona or initially given 6 nights in Ibiza. Using a logistic regression with participant-level random intercepts and controls for the total vacation days and dispersion in vacation days, this paper found that decision makers were significantly more likely to choose an option that had more nights in Ibiza, if their reference point was 6 nights in Ibiza compared with 6 nights in Barcelona ($\beta = 1.17$, $z = 6.90$, $p < .01$). A similar analysis found that there was a significant interaction effect between the number of nights a choice option offers in Ibiza and exposure to the reference point that offered 6 nights in

Ibiza, on the choice probability of that option ($\beta = 1.22$, $z = 20.87$, $p < .01$). Both these findings suggest that the reference points used in this experiment affect participants' choices in favor of the primary attribute in the reference point.

Finally, this paper examined relative preferences for options that were dominated by the reference point (options with some nights at the primary location of the reference point and zero nights in the other location) compared with options that were not dominated by the reference point. The analysis revealed that decision makers displayed a preference for options that were dominated by the reference point ($\beta = 1.92$, $z = 5.70$, $p < .01$), controlling for differences in the total vacation days, dispersion, and relative number of nights in Ibiza, and additionally controlling for participant heterogeneity through random intercepts. This suggests that unfavorable ordinal comparisons with the reference point did not reduce a choice option's preference. This is largely contrary to the predictions of the loss aversion/diminishing sensitivity models of reference dependence.

Model fits. This paper fit the attention and loss aversion/diminishing sensitivity models to the data using the techniques specified at the start of this article. Note that in participant-level fits, one of the loss aversion parameters in LA5 is redundant (as there are losses on only one attribute). Thus, on the participant level, LA5 requires only four parameters. This is taken into account when computing the BIC. Also note that two participants made the majority of their choices without searching for any of the attributes (clicking on any boxes). As these types of choices are excluded in this article's analysis, there is very little data with which to fit the models for these two participants. When discussing individual-level model fits in this section, this paper excludes the fits for these two participants.

Using the BIC to compare the model performance of the simplified models, this paper found that 67% of participants were better fit by AT3 compared with 33% for LA3. Similarly, for the extended models, 63% were better fit by the AT5 compared with 37% for LA5. Overall, the best-performing model of the four models is AT3, which has the lowest median BIC and was additionally able to provide the best fit to 64% of the participants. Model performance is summarized in Table 2. The Appendix presents model performance for extensions and simplifications of LA3 and LA5, and finds that relative fits are largely unchanged.

As in Study 1, this paper also compared the modal predictions for each of the models for each participant in each choice problem (using participant-level best-fit parameters) with the actual choices of the participant. This revealed that the AT3 model was able to accurately predict 78% of all choices, whereas the LA3 model was able to accurately predict 75% of all choices. This is a statistically significant difference when evaluated using a logistic regression ($\beta = 0.22$, $z = 4.99$, $p < .01$). Similarly, the AT5 model was able to accurately predict 86% of all choices, and the LA5 model was able to accurately predict 79% of all choices ($\beta = 0.45$, $z = 9.39$, $p < .01$). Again, this indicates that the best-performing model according to the BIC, AT3, gives a good overall account of the choice data. Figure 5 illustrates this by plotting the aggregated choice probability for Vacation 1 in each of the 83 choices, against the aggregated predicted choice probability for Vacation 1 obtained using participant-level fits for AT3.

Parameters. This paper examined best-fitting parameter values to determine the causes for the differences. These parameters are displayed in Table 2. As in Study 1, the AT3 and AT5 models have reasonable values for their parameters, with relatively high baseline activation and threshold values for AT5. In contrast, the LA3 and LA5 models again display weak diminishing sensitivity and loss aversion. Overall, 54% of participants had a diminishing sensitivity parameter $\alpha > .99$, and 26% had a loss aversion parameter $\lambda < 1.01$ for LA3. Likewise, 27% of participants had $\alpha > .99$ for Barcelona, 46% had $\alpha > .99$ for Ibiza, and 64% of participants had $\lambda < 1.01$ for either Barcelona or Ibiza for LA5 (recall that we only estimated λ for a single attribute for LA5, as there were no losses on the nonendowed attribute). Overall, 67% of participants had either $\alpha > .99$ or $\lambda < 1.01$ for LA3, and 93% of participants had either $\alpha > .99$ or $\lambda < 1.01$ for at least one of the attributes in LA5. Median parameter values again reflect these patterns. As shown in Table 2, the median value of λ for LA5 falls below 1.01, the median value of α for LA3 exceeds 0.99, and the median value of α for Ibiza in LA5 is 0.98. The Appendix displays model fits for variants of LA3 and LA5 without the assumptions of diminishing sensitivity and loss aversion, and consistent with the findings outlined here, finds that these simplified models often outperform LA3 and LA5.

Table 2
Model Fits for Study 2

Model	α_1	λ	α_2		γ	Best	BIC
LA3	1.00 [54%]	1.38 [26%]	—		.91	16%	87.22
LA5	.86 [27%]	1.00 [64%]	.98 [46%]		1.45	7%	81.83
	μ_1	ρ_1	μ_2	ρ_2	θ	Best	BIC
AT3	.76	6.34	—	—	3.67	64%	72.33
AT5	.76	153.40	.80	155.37	4.29	13%	75.25

Note. The parameter values correspond to the median parameters from the fits. "Best" refers to the proportion of participants for which the model provides the strongest fit according to BIC. "BIC" refers to the median BIC values from the best-fitting models. The figures in the squared brackets below the parameters of LA3 and LA5 display the proportion of participants with weak levels of diminishing sensitivity or loss aversion ($\alpha > .99$ or $\lambda < 1.01$, respectively). Attribute 1 corresponds to Barcelona and Attribute 2 corresponds to Ibiza. Note that there was only one loss aversion parameter for LA5 (for either Ibiza or Barcelona), as the choice problems involved losses on only one attribute. Finally, the parameter values are rounded, which is why $\alpha_1 = 1.00$ for LA3 (the true median value of this parameter is .998) and $\lambda_1 = 1.00$ for LA5 (the true median value of this parameter is 1.0001). BIC = Bayesian information criterion.

As in Study 1, the participants for whom LA3 and LA5 had very weak diminishing sensitivity and loss aversion were also better fit by AT3 and AT5. Overall, this paper found that of the 23 participants that displayed reasonable diminishing sensitivity and loss aversion for LA3, only 52% were better fit by AT3 compared with LA3. For the remaining 47 participants who have weak diminishing sensitivity or loss aversion for LA3, 75% were better fit by AT3 compared with LA3. The median differences in the BIC scores for LA3 relative to AT3 are only 1.25 for the first group compared with 12.38 for the second group. These differences are statistically significant when examined with a linear regression ($\beta = 14.46$, $z = 2.17$, $p < .05$).

Likewise, of the five participants that had reasonable diminishing sensitivity and loss aversion for both attributes for LA5, only 40% were better fit by AT5 compared with LA5. For the remaining

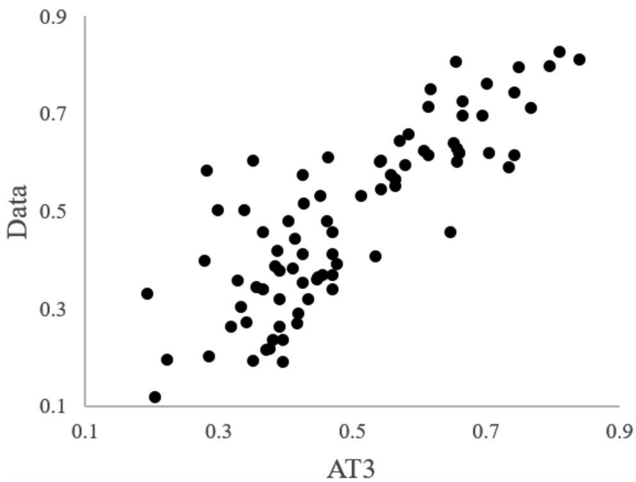

Figure 5. A plot of the aggregated choice probability for Vacation 1 in each of the 83 choices in Study 2, as predicted by participant-level fits for AT3 (the best-performing model according to the Bayesian information criterion).

65 participants who had weak diminishing sensitivity or loss aversion for at least one attribute for LA5, 64% were better fit by AT5 compared with LA5. The median differences in the BIC scores for LA5 relative to AT5 are −3.09 for the first group compared with 3.85 for the second group. These differences do not reach statistical significance ($p > .10$) because of the small sample size of the first group.

Attention. Finally, we can examine attention data for this experiment, obtained through the MouseLAB interface. Recall that attentional theories of reference dependence predict that decision makers should be more likely to attend to the primary attributes of the endowment. Thus, a decision maker whose endowment consists of 6 nights in Ibiza but 0 nights in Barcelona should be more likely to click on the Ibiza attributes of the choice options, and additionally spend more time viewing information about the Ibiza attributes of these options. The opposite should be the case for a decision maker endowed with 6 nights in Barcelona and 0 nights in Ibiza.

This was tested in the data by pooling together the total number of clicks and the total time spent viewing each attribute in each choice problem for each participant. This paper then regressed these clicks and viewing times on a binary independent variable, which captured whether the attribute was contained in the endowment offered to the decision maker. The regressions included participant-level random intercepts to control for participant heterogeneity, as well as a second independent variable that represents the specific attribute in consideration (Ibiza vs. Barcelona).

This paper found that decision makers clicked an average of 2.26 times on an attribute if it was the primary attribute of their endowment, but only an average of 2.22 times if it was not. Although this difference is in the direction predicted by the attentional model, it is not statistically significant ($p > 0.10$). It also found that decision makers spent an average of 2,397 ms viewing an attribute if was the primary attribute of their endowment, but only an average of 2,227 ms if it was not. This is a significant difference ($\beta = 168.91$, $z = 4.15$, $p < .01$), and this difference persists if viewing times are transformed by a logarithmic function ($\beta = 0.05$, $z = 4.17$, $p < .01$).

The viewing time differences documented here provide process-level support for the attentional models of reference dependence. However, can they predict the differences in fits for AT3 and AT5 compared with LA3 and LA5? To test this, this paper pooled trial-level data for each participant to obtain the average difference in viewing times (ADVTs) for the primary attribute of the participant's endowment relative to the primary attribute of the competing option. This measure quantifies the degree to which each participant's attention was biased in favor of the endowment's primary attribute. Participants who spent relatively more time viewing their endowment's primary attribute had positive values on the ADVT variable, whereas participants who spent relatively less time viewing their endowment's primary attribute had negative values on this variable.

This paper regressed the differences in the BIC scores of LA3 and AT3, and LA5 and AT5, for the participants on the ADVT variable. These comparisons did yield a mild positive relationship, suggesting that higher ADVTs leads to better fits for AT3 and AT5, but this relationship was not statistically significant ($p > .10$). This paper also examined this relationship after taking a logarithm of the ADVT values. With the logarithm, it obtained strong significant relationships for both the difference in the BIC of LA3 compared with AT3 ($\beta = 8.72$, $z = 2.91$, $p < .01$), as well as the difference in the BIC of LA5 compared with AT5 ($\beta = 7.24$, $z = 2.03$, $p < .05$). These results suggest that viewing time biases (when transformed logarithmically) can predict relative model fits for the attentional and loss aversion/diminishing sensitivity models.

Discussion

Study 2 compared the attention and loss aversion/diminishing sensitivity theories of reference dependence on a participant level. Each participant was exposed to a single reference point, though this reference point varied across participants. It found that participants were more likely to choose options that had more of their reference point's primary attribute, indicating the presence of a type of endowment effect. Overall, the attentional models outperformed their loss aversion/diminishing sensitivity counterparts in terms of the BIC, indicating a better fit. The best-performing model was AT3, which provided the best description for 64% of all participants, and also had the lowest median BIC.

As in Study 1, these differences were explained by the fact that many participants did not display strong diminishing sensitivity and loss aversion. Additionally, participants with very weak levels of diminishing sensitivity and loss aversion were typically the ones that were better fit by the attentional models. Again, it would be possible to improve the fit of the LA3 and LA5 by not constraining their parameters; however, such models would then be unable to explain all the existing behavioral findings associated with reference dependence (which require both diminishing sensitivity and loss aversion).

Finally, an examination of the mouse-tracking data obtained from this experiment suggested that decision makers were significantly more likely to spend time viewing attributes of their endowment. Additionally, this tendency was positively related with model fits, so the participants with the greatest attentional biases were also the ones that were better fit by AT3 and AT5 compared with LA3 and LA5. Overall the choice data, model fits, and attention data all support the attentional theory of reference dependence.

General Discussion

There are two contrasting theories of reference-dependent choice. The traditional explanation for this phenomenon, based on the assumptions of prospect theory, proposes that decision makers process choice options in terms of gains and losses relative to the reference point. Changing reference points affects perceived gains and losses. Because of diminishing sensitivity in gains and losses as well as loss aversion, this can alter choice (Köszegi & Rabin, 2006; Tversky & Kahneman, 1991). In contrast, a second explanation supported by process-level data proposes that reference points influence the decision maker's attention in a choice task. Changing reference points alters attention toward different attributes, affecting the accumulation of preference, and generating the observed reference-dependent choice biases (Bhatia, 2013; Carmon & Ariely, 2000; Johnson et al., 2007).

In Study 1, this paper quantitatively compared the behavioral predictions of these two theories of reference dependence. It obtained multiple choices from participants and found that the majority of the participants in the experiments were better described by attention models compared with loss aversion/diminishing sensitivity models. Study 2 replicated these findings while providing further process-level data in support of the attentional theory of reference dependence.

Quantitative Comparisons

Thus far, there have been no attempts to quantitatively fit and compare different riskless reference-dependent theories using choice predictions. Tversky and Kahneman (1991), for example, discuss a number of behavioral effects associated with reference dependence and additionally qualitatively explain how loss aversion/diminishing sensitivity models can capture these effects. However, they do not attempt to recover the parameters of their models using quantitative fits to the data. Likewise, although Bhatia (2013) proposes such a model, his emphasis is on using his model to qualitatively capture the effects of Tversky and Kahneman, Herne (1998), and others, and not mathematically fit his model to reference-dependent choice data. Indeed, the endowment effect, improvements versus trade-offs effect, and the advantages and disadvantages effect, outlined at the start of the article, are all qualitative effects involving changes in preferences as reference points are varied. Theories that account for these effects have typically only attempted to predict relative choice probabilities, and not absolute choice probabilities.

Ultimately, the main descriptive goal of all reference dependence theories is to predict choice, and evaluating the quantitative fit of a model to choice data provides a rigorous approach to testing the model's predictions. Such evaluations are also useful for examining the predictive power of different theories when these theories make the same qualitative or directional predictions (as loss aversion/diminishing sensitivity and attention do for existing effects). By using quantitative fits to compare the attentional and loss aversion/diminishing sensitivity theories of reference dependence, this article fills a much-needed void in psychological research on reference dependence.

Quantitative fits to choice data can also be used to explain why some theories are worse than others at predicting choice, and an examination of the best-fitting parameters in the experiments reveals some critical issues with the loss aversion and diminishing sensitivity mechanisms. In general, this paper finds that many participants have loss aversion and diminishing sensitivity parameter values very close to 1, indicating that had these parameters not been constrained, the fitted models would display loss seeking or increasing sensitivity. Importantly, participants with these types of parameters were also the ones that were better fit by attentional models of reference dependence. Of course, we could have improved the fits of the loss aversion/diminishing sensitivity theory by removing parameter constraints, but this would have then violated the key assumptions necessary to explain existing behavioral effects (such as the endowment effect, the improvement vs. trade-offs effect, the advantages and disadvantages effect, and their extremity-based moderators), which rely critically on both loss aversion and diminishing sensitivity.

Overall, the results suggest that the loss aversion/diminishing sensitivity theory may not be able to describe all types of reference-dependent choice behaviors. Although its assumptions are suitable for describing reference dependence when the available choice options are superior to the reference points (as with preexisting data), these assumptions cannot quantitatively predict choices when the options are inferior to the reference point. The attention theory of reference dependence, in contrast, appears to provide a good account of behavior in both these settings.

Process-Level Data

There is, by now, considerable process-level data that supports the attention theory of reference dependence. For example, Carmon and Ariely (2000) found that individuals tend to focus on the attributes that they will forgo, rather than the ones that they will gain. The attributes that will be foregone are precisely those that are contained in the endowed option, as assumed by the attention theory tested in this article. Likewise, Nayakankuppam and Mishra (2005) discovered that individuals are more likely to attend to the positive aspects of their endowed objects. Given that the endowed options in their experiment are desirable goods containing largely positive attributes, this finding is consistent with the assumption that reference points increase the activation of their component attributes. Johnson et al. (2007) also found that individuals tend to think about the primary aspects of their endowed objects before attending to other attributes relevant to the decision task. As with Carmon and Ariely, and Nayakankuppam and Mishra, Johnson et al. (2007) note that the number of recalled attributes related to the endowed good is greater than the number of recalled attributes not related to the endowed good. Results similar to these have also been shown for external information search using mouse tracking (Willemsen et al., 2011) and eye tracking (Ashby et al., 2015).

Study 2 provides further process-level data in support of the attentional theory. It used a mouse-tracking interface to observe the attributes attended to by decision makers prior to making their choices. As with prior work, the analysis of Study 2 data reveals that decision makers were more likely to attend to the primary attributes of their endowments. This paper also found that participant-level attentional biases predicted the relative quantitative fits of the two theories to the participants: Ultimately, participants that were especially likely to attend to the endowment's attributes were also those who are better fit by the attentional models relative to the loss aversion/diminishing sensitivity models. This second level of analysis draws a close link between process-level observations (which test the psychological mechanisms underlying a given theory) and quantitative fits (which test the ability of the theory to describe choice data), and shows that the quantitative power of the attentional theory stems directly from its hypothesized psychological mechanism.

Attention in Other Domains

Memory and attention is considered to play a very important role in decision making (Kahneman, 2003; Weber & Johnson, 2006), and biases in attribute activation have been shown to explain a number of behavioral findings. These findings include the anchoring effect, focus of comparison effects, and constraint satisfaction effects (Chapman & Johnson, 1999; Dhar & Simonson, 1992; Dhar, Nowlis, & Sherman, 1999; Glöckner, Betsch, & Schindler, 2010; Holyoak & Simon, 1999; Houston, Sherman, & Baker, 1989; Strack & Mussweiler, 1997). For all these effects, especially, salient alternatives bias attribute and cue activation in a manner similar to that assumed by the attentional theory of reference dependence. Additionally, as with the attentional theory, these biases in attribute and cue activation affect choice, generating preference reversals and other deviations from economic rationality.

Memory and attention biases are also at play in various judgment and reasoning tasks. For example, similarity comparisons are systematically biased by the concept that is subject of the comparison. It is this concept that determines the attributes that are attended to, and subsequently, the outcome of the similarity judgment (Tversky, 1977). Likewise, focal hypotheses tend to increase the accessibility of information that is positively associated with these hypotheses (Klayman & Ha, 1987). Finally, biases in attribute activation caused by associations with the judgment task have been shown to account for a number of fallacies involving probabilistic inference and induction (Kahneman, 2003; Sloman, 1996).

Of course, the idea that attention affects cognitive processing is not at all unique to judgment and decision-making research. Feature (or sematic) priming plays an important role in a number of other psychological domains, including semantic memory, visual perception, and lexical decision making. Indeed, this type of priming can be seen as one of the key properties of human cognition and behavior, one which naturally influences preferential choice in the presence of salient reference points.

What Are Reference Points?

Although the importance of reference points in determining choice has been acknowledged for a long time, there is still some debate about what reference points actually are. Current endowments (Knetsch, 1989; Knetsch & Sinden, 1984; Thaler, 1980), past endowments (Strahilevitz & Loewenstein, 1998), the endowments of neighbors and close others (Clark & Oswald, 1996), the status quo (Samuelson & Zeckhauser, 1988), aspirations (Heath et al., 1999), expectations (Abeler, Falk, Goette, & Huffman, 2011; Köszegi & Rabin, 2006), and focal outcomes in the choice task (Bushong et al., 2010; Dhar et al., 1999; Dhar & Simonson, 1992; Krajbich et al., 2010) have all been shown to drive reference-dependent choice.

The discussion on the role of attention in judgment, decision making, and other areas of psychology offers a simple definition of a reference point. According to the attentional theory, any choice option that is more salient than the other options in the choice set will operate like a semantic (or feature) prime, and exert a strong influence on attribute activation. This will alter the attention toward attributes in the decision task and bias final preferences. By this definition, any exceptionally salient option is a reference point, and will generate the endowment effect, the improvements versus trade-offs effect, the advantages and disadvantages effect, and other reference-dependent phenomena.

This definition can be used to extend attention to study choice set dependence. Preferences are strongly influenced by available, yet irrelevant, options. Adding, removing, or otherwise changing these options can alter the decision maker's choices and lead to a range of preference reversals (Huber et al., 1982; Simonson, 1989). If a reference point is merely a choice option that is exceptionally salient, and we assume that available options are more salient than those not in the choice set, then we can consider choice set dependence to be a special case of reference dependence, in which every available option acts as a reference point. We can subsequently use the attention theory of reference dependence to make predictions regarding choice set effects in preferential choice. Indeed, Bhatia (2013) shows that such an approach can provide a comprehensive account of a very large range of findings regarding choice set dependence, including context effects (Huber et al., 1982; Simonson, 1989; Tversky, 1972), alignability effects (Markman & Medin, 1995; Slovic & MacPhillamy, 1974), less-is-more effects (Hsee, 1998; Simonson, Carmon, & O'Curry, 1994), and related process-level findings (Pettibone, 2012; Zhang & Markman, 2001). Of course, there are some such effects that prospect theory approaches, such as the one discussed here, have also been applied to (e.g., Tversky & Simonson, 1993; Usher & McClelland, 2004). Bhatia (2013) outlines similarities and differences between attentional accounts of choice set dependence and prospect theory accounts of reference dependence.

Beyond Prospect Theory

The tests presented in this article are not the first to challenge prospect theory accounts of choice behavior. Closely related quantitative tests were performed by Rieskamp (2008) for the domain of risky choice. As in the current article, Rieskamp compared prospect theory with decision field theory (Busemeyer & Townsend, 1993), a prominent preference accumulation model. Indeed, much of the structure and the techniques in this article relate directly to those outlined in Rieskamp, and just like Rieskamp, this article finds that accumulation models outperform models based on the assumptions of prospect theory.

More generally, the notion that decision makers make risky decisions using prospect theory has been refuted by a number of researchers (see Birnbaum, 2008, for a discussion). Others have directly questioned prospect theory's assumption of loss aversion (Erev, Ert, & Yechiam, 2008; Ert & Erev, 2013; Harinck, Van Dijk, Van Beest, & Mersmann, 2007; Yechiam & Telpaz, 2013). Indeed, much of this work suggests that attention may be the driving mechanism underlying the effects that prospect theory was initially formulated to explain (see, e.g., Bhatia, 2014; Birnbaum, 2008; Yechiam, & Hochman, 2013a, 2013b). The findings in this paper complement this risky choice research, and suggest that the main assumptions of prospect theory also fail to adequately describe riskless multiattribute choice, and additionally that attentional mechanisms may be compelling alternatives to mechanisms such as loss aversion. Note that a similar argument is outlined in Trueblood (2015), who finds that multiattribute reference point effects also emerge in perceptual decision making, a domain in which loss aversion is unlikely to play a role.

These criticisms of prospect theory also suggest a way forward. Prospect theory was initially proposed as a mathematical description of choice behavior. Although the approach it presented was no doubt revolutionary, it nonetheless failed to formally incorporate the effect of basic cognitive processes, such as memory, attention, and information search and accumulation. These processes play a crucial role in decision making and, as shown in this article, are able, by themselves, to predict many of the behaviors that prospect theory was formulated to explain. Future work should attempt to test the effects of these basic cognitive processes in other decision-making settings, so as to provide a comprehensive, cognitively grounded framework for studying preferential choice.

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Appendix

Additional Tests

Model Extensions

The loss aversion/diminishing sensitivity models examined in this article do not permit explicit attribute weights, nor do they allow the diminishing sensitivity parameter to vary across gains and losses. As discussed in the article, this prevents parameter interaction and facilitates model comparison. This appendix, however, considers models which have these features. Particularly, it extends LA5 to allow for separate weights for each attribute. This model retains the assumptions of Equation 1 and 3 (in the main text), but replaces Equation 2 with

$$U(\boldsymbol{x}|\boldsymbol{r}) = \pi \cdot U_1(x_1|r_1) + (1-\pi) \cdot U_2(x_2|r_2) \qquad \text{(A1)}$$

Here, π represents an explicit attribute weight on Attribute 1 versus Attribute 2. To ensure that the model is well defined this paper restricts π to the range [0, 1]. As there are six parameters in the resulting model, this is referred to as LA6.

This paper also considers an extension of LA5 to allow for separate diminishing sensitivity parameters for gains and losses. This model retains the assumptions of Equation 1 and 2 (in the main text), but replaces Equation 3 with

$$U_i(x_i|r_i) = \begin{cases} (x_i - r_i)^{\alpha_i} & \text{if } x_i \geq r_i \\ -\lambda \cdot (r_i - x_i)^{\beta_i} & \text{if } r_i > x_i \end{cases}. \qquad \text{(A2)}$$

Here α_i represents the diminishing sensitivity parameter for attribute i in gains, and β_i represents the diminishing sensitivity parameter for attribute i in losses. As in the main text, this paper restricts $0 < \alpha_i < 1$ and $0 < \beta_i < 1$, to ensure diminishing sensitivity. This model has seven parameters and is referred to as LA7.

Finally, this paper considers a hybrid model which combines the assumptions of LA6 and LA7. This model has both explicit attribute weights and differing diminishing sensitivity for gains and losses. It retains the assumptions of Equation 1 (in the main text), but replaces Equations 2 and 3 with Equations A1 and A2 defined here. This model has eight parameters and is referred to as LA8.

Now, this paper fit LA6, LA7, and LA8 to the data from Study 1 and 2 using the methods outlined in the main text. The fits for these models (as well as for LA3, LA5, AT3, and AT5) are displayed in Table A1. As can be seen in this table, the relative fits for the attentional and loss aversion/diminishing sensitivity models persist even when we permit three additional extensions to LA5. As in Study 1, AT5 is the best-performing model in terms of both median BIC and the proportion of participants best fit by the model. Likewise, for Study 2, AT3 is the best-performing model according to these two metrics.

Table A1
Model Fits for Study 1 and 2 With Extended Loss Aversion/Diminishing Sensitivity Model

	Study 1		Study 2	
Model	Best	BIC	Best	BIC
LA3	9%	174.96	15%	87.22
LA5	4%	85.24	6%	81.83
LA6	11%	74.80	1%	84.73
LA7	0%	92.10	1%	87.83
LA8	0%	82.98	0%	89.15
AT3	4%	173.71	64%	72.33
AT5	72%	68.05	13%	75.25

Note. "Best" refers to the proportion of participants for which the model provides the strongest fit according to BIC. "BIC" refers to the median BIC values from the best-fitting models. BIC = Bayesian information criterion.

(*Appendix continues*)

Table A2
Model Fits for Study 1 and 2 With Simplified Loss Aversion/Diminishing Sensitivity Model

	Study 1		Study 2	
Model	Best	BIC	Best	BIC
LA3	1%	174.96	1%	87.22
LA5	4%	85.24	3%	81.83
$LA2_{DS}$	4%	172.66	4%	119.39
$LA4_{DS}$	0%	100.29	10%	84.13
$LA2_{LA}$	7%	171.60	19%	84.30
$LA4_{LA}$	5%	94.41	0%	88.72
AT3	3%	173.71	53%	72.33
AT5	76%	68.05	10%	75.25

Note. "Best" refers to the proportion of participants for which the model provides the strongest fit according to BIC. "BIC" refers to the median BIC values from the best-fitting models. BIC = Bayesian information criterion.

Model Simplifications

This paper also considers simplifications to the LA3 and LA5 models that individually avoid the assumptions of loss aversion or diminishing sensitivity. Examining these models is useful for testing the degree to which these assumptions are violated in the data: If we find that the simplified models outperform LA3 and LA5, then we can more rigorously state that the participants do violate display loss aversion or diminishing sensitivity. This would complement the findings outlined in the main text, which show that best-fitting LA3 and LA5 models often have $\alpha > .99$ or $\lambda < 1.01$. Note that these simplified models, by avoiding loss aversion or diminishing sensitivity, would no longer be able to capture the existing findings on reference dependence, such as those displayed in Figure 1.

There are four simplified models that this paper considers. The first two retain the assumption of diminishing sensitivity, $0 < \alpha < 1$, but restrict $\lambda = 1$. These models, referred to $LA2_{DS}$ and $LA4_{DS}$, have two and four parameters, respectively. $LA2_{DS}$, like LA3, assumes a single flexible α for both dimensions, whereas $LA4_{DS}$, like LA5, allows α to differ across dimensions. The second two models this paper examines here retain the assumption of loss aversion, $\lambda > 1$, but restrict $\alpha = 1$. These models, referred to $LA2_{LA}$ and $LA4_{LA}$, have two and four parameters, respectively. $LA2_{LA}$, like LA3, assumes a single flexible λ for both dimensions, whereas $LA4_{LA}$, like LA5, allows λ to differ across dimensions.

Now, this paper fit $LA2_{DS}$, $LA4_{DS}$, $LA2_{LA}$, and $LA4_{LA}$ to the data from Study 1 and 2 using the methods outlined in the main text (note that as Study 2 does not need separate loss aversion parameters for the two dimensions, $LA4_{LA}$ has only three parameters for this study). The fits for these models (as well as for LA3, LA5, AT3, and AT5) are displayed in Table A2. As can be seen in this table, the relative fits for the attentional and loss aversion/diminishing sensitivity models persist even when we permit these simplifications to LA3 and LA5. As in Study 1, AT5 is the best-performing model in terms of both median BIC and the proportion of participants' best fit by the model. Likewise, for Study 2, AT3 is the best-performing model according to these two metrics.

Additionally, in Study 1, $LA2_{DS}$ and $LA2_{LA}$ both outperform LA3 in terms of BIC and proportion of participants best fit by the model. The results for LA5 are mixed: It outperforms $LA4_{DS}$ and $LA4_{LA}$ in terms of median BIC, but $PT4_{LA}$ does provide the best fit for more participants. Similarly, in Study 2, $LA2_{LA}$ outperforms LA3 in terms of BIC and both $LA2_{LA}$ and $LA2_{DS}$ outperform LA3 in terms of proportion of participants best fit by the model. LA5 does outperform $LA4_{DS}$ and $LA4_{LA}$ in terms of median BIC, but $LA4_{DS}$ provides a best fit for more participants. Note that the discrepancy between relative fits when evaluated using median BIC and when evaluated using proportion of participants best fit is because of the fact that participants who have lower BIC scores for LA5 are often *best* fit by AT3 or AT5. If we only compare the proportion of participants *better* fit by $LA4_{DS}$ versus LA5 or *better* fit $LA4_{LA}$ versus LA5, the results are consistent with the median BIC measures.

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