Range-Dependent Attribute Weighting in Consumer Choice: An Experimental Test

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Abstract

This paper investigates whether the range of an attribute's outcomes in the choice set alters its relative importance. I derive distinguishing predictions of two prominent theories of range-dependent attribute weighting: the focusing model of Kőszegi and Szeidl (2013) and the relative thinking model of Bushong, Rabin, and Schwartzstein (2021). I test these predictions in a laboratory experiment in which I vary the prices of high- and low-quality variants of multiple products. The data provide clear evidence of choice-set dependence consistent with relative thinking: price increases that expand the range of prices in the choice set lead to *more* purchases. Structural estimates imply economically meaningful effect sizes: the average participant was willing to pay around 17% more when a seemingly irrelevant option is added to their choice set.

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Theories of range-dependent attribute weighting propose that an attribute's importance depends on its range of outcomes in the choice set. For example, an individual deciding between two options can be swayed by the availability of an inferior third option if it alters the range of price and quality. Two recent theories make conflicting assumptions about how an attribute's range affects its importance. Kőszegi and Szeidl (2013) (henceforth KS) propose a theory of "focusing" in which individuals overweight attributes that have the widest range of values in the choice set. In contrast, the "relative thinking" model of Bushong, Rabin, and Schwartzstein (2021) (henceforth BRS) assumes that fixed differences between attribute values appear larger when compared to a relatively narrow range of possible values in the choice set. Both focusing and relative thinking offer plausible frameworks for explaining and predicting when violations of the independence of irrelevant alternatives (IIA) assumption might arise. In practice, little is known about whether range weighting generates systematic departures from IIA in simple consumer choice situations or whether any such deviations are driven by the focusing or relative thinking mechanism.

This lack of empirical clarity is problematic given the broad economic implications of range weighting. For example, range weighting can shed light on why it may be optimal for firms to offer product lines that can be hard to rationalize from the neoclassical perspective. Firms can leverage premium or add-on options, such as a reserve bottle of wine or a first class airline upgrade, to decrease consumers' price sensitivity. Even if these options are rarely chosen, they can boost sales by making standard options more appealing. In principal-agent settings, range weighting can explain why bonus schemes sometimes backfire: bonuses for exerting high effort might alter agents' responsiveness to rewards and induce lower effort. More generally, demand estimation may be systematically biased if range weighting is not taken into account: price changes that alter the price range can attenuate or amplify the overall price sensitivity estimates.

This paper tests the distinguishing predictions of focusing and relative thinking by investigating experimentally how the range of outcomes within the choice set impacts how individuals weigh different attributes. The experimental design focuses on situations in which individuals choose between a high- and low-quality variant of a product, with the option of not buying either. I set prices such that one option is clearly inferior but nonetheless influences the relative preference for the remaining two options by affecting the attribute weights. This creates three potential price regions in which range weighting is identified: each region is defined by which one of the three options is irrelevant from the perspective of surplus maximization. Intuitively, changes in the price range generate unique shifts in the agent's willingness-to-pay when the surplus on offer is fixed.

In a lab experiment, I individually calibrate and vary the prices of high- and low-quality variants of multiple products to generate independent variation in the relative attribute ranges and the surpluses on offer. The key innovation of the design is to use the range-weighting comparative statics to tailor the choice sets that participants face. For each decision that participants make, there is always a choice that is inconsistent with one of the two range theories. I show that this environment provides ideal variation to test the nonparametric predictions of focusing and relative thinking, and for estimating the structural parameters of the attribute-weighting function.

The experimental results provide clear evidence of choice-set dependence consistent with relative thinking. First, I reject utility maximization under very general conditions: price increases that expand the price range in the choice set lead to *more* purchases. Second, I show that choice probabilities respond to price changes in manner consistent with the key assumptions of relative thinking. Expanding the price range makes participants more likely to buy the nondecoy option and less likely to not buy. Increasing the price level while holding the price difference between two options fixed causes substitution to higher-quality options. These patterns of demand are consistent with the idea that wider price ranges lead to lower price sensitivity.

I complement this nonparametric analysis with structural estimation of the attribute-weighting function. While this approach requires some parametric assumptions, it allows me to quantify the impact of range weighting in terms of foregone surplus. My estimates imply large aggregate deviations from the neoclassical model due to range-dependent attribute weighing: on average, participants were willing to pay around a 17% premium relative to their intrinsic value due to the presence of seemingly irrelevant options in the choice set. Regardless of the empirical approach or subsample restriction, I find consistent evidence of relative thinking and stable parameter estimates.

Using both nonparametric and structural approaches, I document that between 60 and 75% of participants are best characterized as relative thinkers. Participants that are not best classified as relative thinkers make noisier decisions and do not respond to price increases in a manner consistent with focusing. The structural estimates show that there is substantial individual heterogeneity in the magnitude but not the direction of range weighting. Overall, I find that the majority of participants make choices consistent with relative thinking and no evidence that a nontrivial share of respondents make choices consistent with focusing.

I address three concerns that could affect the interpretation of my results. First, quality is uncertain and may have been misspecified. A particular concern is that participants interpreted prices as signals of quality. I show that both the nonparametric evidence and quantitative estimates of relative thinking are robust to controlling for price signaling. Second, the within-subject nature of the experimental price variation creates the potential for choice-set spillovers across trials. Using several approaches, I show that such spillovers are small and do not alter the results. Finally, an alternative approach to choice-set dependence called salience theory (Bordalo, Gennaioli, and Shleifer, 2013) shares some similar intuitions to relative thinking and might provide a better fit to the data. I show that for a subset of prices in which relative thinking and salience theory make distinguishing predictions, the data continue to support relative thinking and are inconsistent with salience theory. I also show that a generalization of the pairwise normalization model of Landry and Webb (2021) makes the same predictions as relative thinking in my experimental context—thus, my results are also consistent with this model.

This paper makes several contributions to the literature. It is one of the first papers to test the predictions of focusing and relative thinking in simple consumer choice contexts, and the first to estimate the structural parameters of these models. A prior experiment by Andersson, Ingebretsen Carlson, and Wengström (2016) found mixed evidence of range-dependent weighting in an intertemporal choice context: they show that expanding the range of immediate payments leads to more impatient choices, but expanding the range of future payments does not induce more patient choices. A contemporaneous study by Dertwinkel-Kalt et al. (2021) finds evidence for a bias toward payments concentrated in a single period—a behavior consistent with focusing.[1] My results do not necessarily contradict this evidence.

[1]One limitation of these studies is that applications of range weighting to intertemporal choice require further assumptions about how time is represented as an attribute. As such, the results can speak only to KS's representation of intertemporal choice and cannot distinguish this approach from BRS. In contrast, I consider a simple choice context in which both theories make clear testable predictions that are derived assuming only the basic proprieties of the attribute-weighting function.

The choice task faced by participants in my experiment was relatively simple; they had to evaluate only three options, one of which was an outside option of not buying. Each option varied in only two attributes: quality and price. BRS suggest that relative thinking may apply in simple environments, while focusing may dominate in complex settings where attention is stretched and individuals must selectively hone in on certain attributes. My results support this idea: relative thinking is ubiquitous in perhaps the simplest conceivable choice setting in which range weighting is identified.

In a more recent experiment, BRS test the qualitative predictions of relative thinking versus focusing in a real-effort context. They find that respondents prefer to work more when the range of effort costs are wide relative to the range of monetary payments. Their results provide further support for the key assumption of relative thinking: fixed differences appear larger when compared to a narrow range of outcomes in the choice set. My structural estimates quantify the implications of this assumption in terms of foregone surplus and find substantial heterogeneity across individuals.

Finally, this paper contributes to a large literature that has documented choice-set effects in marketing and psychology. Traditionally, choice-set dependence has been demonstrated in forced choice amongst three options with a dominated or near-dominated "decoy" option (Huber, Payne, and Puto,1982; Huber and Puto, 1983). My experimental design generalizes the concept of a decoy option: in addition to demonstrating classic asymmetric dominance effects, I show that superior quality options and not buying can serve as decoys. More importantly, I also quantify the impact of decoy options in terms of a surplus premium and find economically meaningful changes in willingness-to-pay due to their presence.

1 Theoretical Framework

This section describes a general model of range-dependent attribute weightings that nests focusing and relative thinking. I demonstrate that range-based attribute weights are identified in a common economic situation: choosing between a high- and a low-quality variant of a product, along with the option of not buying. I also derive the distinguishing predictions of the focusing and relative thinking models, and outline the key comparative statics that the experiment tests.

1.1 Basic Setup

Consider an agent who is making a one-time decision about which of $j = 1, ..., J$ vertically differentiated options to choose. Let q_j denote the quality of option j in monetary terms; this can be thought of as the agent's intrinsic value for j, absent any choice-set influences. A choice set is $\mathcal{C} = \{(q_j, p_j)_{j=1}^{J}\}$, where $p_j \in \mathbb{R}_+$ is the price of j. Utility maximization is based on on the following assumptions.

A1. *(Utility Maximization). The utility of option j is increasing in q_j, decreasing in p_j, and independent of (q_k, p_k) for all $k \neq j$.*

A1 states that agents like higher-quality options, dislike paying higher prices, and that their evaluation of each option j is independent of other options in the choice set. In illustrative examples and parametric estimation, I will sometimes use the following specific form of utility maximization.

A2. *(Surplus Maximization). The utility of option j is $U_j = q_j - p_j$.*

According to A2, agents simply compare the difference between quality and price for each option, and choose the one with the largest surplus. In contrast to utility maximization, models of choice-set dependence propose that any option $k \neq j$ in the choice set can directly affect the utility of j by altering how agents weight each attribute. The focusing model of Kőszegi and Szeidl (2013) and the relative thinking model of Bushong, Rabin, and Schwartzstein (2021) both assume that an attribute's weight depends on its range of outcomes within the choice set.

While both focusing and relative thinking assume that the range determines attribute importance, they make opposite assumptions about the direction of the effect. Focusing assumes that attributes with the widest range of values in the choice set receive the largest decision weights. A psychological intuition for focusing is that people have limited attention and therefore focus on the attributes that vary the most across options. Motivation for this assumption comes from Schkade and Kahneman (1998), who examined life satisfaction ratings and found that people "focus on salient differences" (p. 344) such as the weather in California versus the Midwest. Conversely, relative thinking assumes that a fixed amount appears larger when compared to a relatively narrow range. Thaler (1999) conveys the intuition for this assumption by drawing on insights from psychophysics: "\$50 will appear larger by itself than in the context of a much larger bill" (p. 193).

A3. *(Range Weighting): The utility of option j is $V_j = g(\Delta_q;\gamma)\cdot q_j - g(\Delta_p;\gamma)\cdot p_j$ where $\Delta_x \equiv \max_j x_j - \min_j x_j$ is the range of attribute $x\{q,p\}$ in choice set $\mathcal{C}$ and the weighting function g satisfies the following properties:*

i. g is continuously differentiable in both Δ and γ and $\lim_{\Delta\to 0}\Delta\cdot g(\Delta;\gamma) = 0$
ii. $\Delta g(\Delta;\gamma)$ is strictly increasing in Δ
iii. For any $\Delta_1 > \Delta_2$, $g(\Delta_1;\gamma)/g(\Delta_2;\gamma)$ is strictly increasing in γ

A3 provides a general characterization of range-dependent attribute weighting. The weighting function g can be increasing, decreasing, or constant, thereby nesting focusing, relative thinking, and surplus maximization respectively. Part (ii) imposes some limit on the extent of range-weighting in the case where g is decreasing. It implies, for example, that agents must prefer \$2 evaluated against a range of \$2 over \$1 evaluated against a range of \$1. This is an implication of focusing, whereas BRS impose it as an additional assumption.

Part (iii) of A3 establishes that a single parameter γ indexes the direction and magnitude of range weighting. A larger γ leads to a relative increase in the weight attached to the attribute with the wider range. Without loss of generality, I normalize $\gamma = 0$ to represent the case of surplus maximization. A negative value for γ then implies range weighting consistent with relative thinking, with the limiting case of $\gamma = \underline{\gamma}$ characterized by a preference for ratios: $g(\Delta_1;\underline{\gamma})/g(\Delta_2;\underline{\gamma}) = \Delta_2/\Delta_1$.[2] Positive γ values indicate focusing, and, in the limiting case of $\gamma = \overline{\gamma}$, individuals only pay attention to the attribute with the widest range within the choice set: $g(\Delta_1;\overline{\gamma})/g(\Delta_2;\overline{\gamma}) = \infty$. Part (i) provides mild technical conditions necessary for establishing identification of the range-weighting parameter γ.

To illustrate the predictions of range weighting and to facilitate structural estimation, I will sometimes adopt the following parametric weighting function.

A4. *(Parametric Range Weighting): $g(\Delta_x;\gamma) = (\Delta_x)^\gamma$ where $\gamma \in (-1,\infty)$*

The weighting function A4 provides a simple characterization of range weighting. Surplus maximization is nested in this specification by $\gamma = 0$, focusing by $\gamma \in (0,\infty)$, and relative

[2]This is the limiting case implied under the assumption that $\Delta\cdot g(\Delta;\gamma)$ is strictly increasing in Δ.

thinking by $\gamma \in (-1, 0)$. In Section 1.2, I use this parametric form to illustrate graphically the key predictions of range weighting and my approach to identification. My structural estimation in Section 4 also uses this parametric form. However, I demonstrate in Section 1.3 that identification of γ holds for the more general specification of the attribute-weighting function in A3. Moreover, in Section 1.4 I derive the main comparative-statics predictions of utility maximization and range weighting using only A1 and A3. Therefore my primary tests are based on the nonparametric specifications in A1 and A3 and do not rely on the specific functional forms in A2 and A4.

1.2 Predictions and Identification

I derive the predictions of range-dependent attribute weighting in two simple contexts: two- and three-option choice sets. In each context, I focus on situations in which individuals choose between a high-quality h and a low-quality l variant of a product, with fixed qualities q_h and q_l and where $q_h > q_l$. The contexts differ in whether the option to not buy is available. I assume that not buying has zero quality and is costless. I then investigate how predicted choices depend on the price pairs (p_h, p_l) that people face.

Roughly speaking, two forces motivate range-weighting agents: obtaining surplus and the influence of overweighted attributes in choice sets. In practice, γ is identified when these two forces come into sufficient conflict, such that surplus maximization and range weighting make different predictions. Formally, identification requires that changes in γ lead to unique changes in predicted choices. The remainder of this section illustrates which choice sets and prices lead to distinct predictions and formalizes the identification argument. I assume the parametric forms A2 and A4 hold for surplus maximization and range weighting respectively. In Sections 1.3 and 1.4, I show that the predictions and identification hold nonparametrically.

Consider first a binary choice between h and l. In this context, changes in γ do not lead to changes in choices, and therefore γ cannot be identified. To see this, note that option h will be preferred whenever $(\Delta_q)^\gamma q_h - (\Delta_p)^\gamma p_h \geqslant (\Delta_q)^\gamma q_l - (\Delta_p)^\gamma p_l$. For the non-trivial case where $p_h > p_l$, this condition can be rewritten as $(\Delta_q)^{1+\gamma} > (\Delta_p)^{1+\gamma}$, which holds if and only if the surplus on h exceeds that on l. Therefore, surplus maximization and range weighting make the same predictions in this context.[3] It is therefore possible to obtain

[3]In Appendix A, I show that this holds nonparametrically under weak regularity conditions on the range-

proxies for quality in this environment. In particular, when evaluating a product with quality q in isolation, range-weighting agents will buy if $p < q$, will not buy if $p > q$, and will be indifferent at $p = q$.

Now suppose that the option of not buying either product, o, is also available and therefore the choice set is $\mathcal{C}(p_h, p_l) = \{(q_h, p_h), (q_l, p_l), (0, 0)\}$. Note that because the qualities are fixed, the prices of h and l define the choice set. Identification of γ therefore hinges on how predicted choices vary as a function of these prices.

Figure 1 depicts optimal choices for a surplus maximizer ($\gamma = 0$) facing choice sets of the form $\mathcal{C}(p_h, p_l)$ as a function of p_h and p_l. The solid black lines depict indifference boundaries: that is, price pairs such that the agent is indifferent between the two adjacent options. A surplus maximizer will choose l whenever it has a positive surplus ($p_l < q_l$) and its price difference with h is greater than the quality difference ($p_h - p_l > q_h - q_l$). This occurs in the top-left region of the (p_h, p_l) space. In the bottom-right region, surplus maximizers prefer h as it has a positive surplus ($p_h < q_h$) that is greater than that of l, ($p_h - p_l < q_h - q_l$). In the top-right region, both h and l have a negative surplus, ($p_l > q_l$ and $p_h > q_h$), and hence not buying is optimal.

Changes in γ will impact the location of these boundaries in the price space. The range of quality is set solely by the high-quality option, $\Delta_q = q_h$, while the price range is determined by whichever price is highest, $\Delta_p = \max\{p_h, p_l\}$. Figure 2 depicts the indifference boundaries under focusing in panel (a) and relative thinking in panel (b).

First, consider how γ impacts the boundary between buying l and not buying. In the area surrounding this boundary, the price range ($\Delta_p = p_h$) exceeds the quality range ($\Delta_q = q_h$). According to focusing, this causes agents to overweight prices relative to quality. As not buying is cheaper than l, focusing agents become more likely to not buy: hence, the indifference set shifts to the left as depicted in the top-left area of panel (a). Conversely, relative thinking assumes that the wider price range makes agents less price sensitive, and therefore more likely to purchase l. This causes the indifference boundary to shift to the right, as depicted in panel (b).

weighting function (see Proposition 4). This result relates to the discussion of balanced choices in both KS and BRS; the authors show that if h has a higher quality but also a higher price, then the surplus maximizing choice will prevail. I show that equivalence between surplus maximization and range-weighting extends to all possible price pairs $(p_h, p_l) \in \mathbb{R}^2_+$ in the two-attribute case.

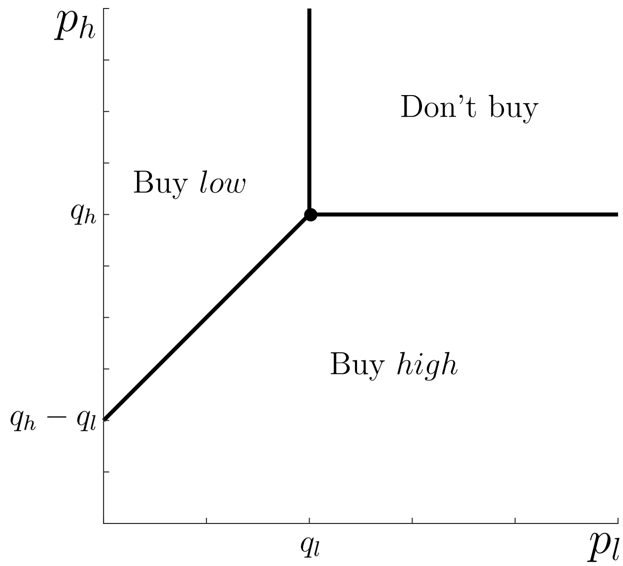

Figure 1: Optimal choices as a function of (p_h, p_l) for a surplus-maximizing agent choosing between a high- and low-quality variant of a product along with the option to not buy. The qualities of the high- and low-variants are fixed and denoted by q_h and q_l.

A similar intuition extends to the region surrounding the boundary between buying h and not buying. This boundary will shift when option l sets the price range, $p_l > p_h$, and the price range ($\Delta_p = p_l$) exceeds the quality range ($\Delta_q = q_h$). According to focusing, this leads to heightened price sensitivity and a downward shift in the *h*-*o* boundary. Relative thinking predicts that agents become less price sensitive and therefore more likely to buy h. This causes an upward shift in the *h*-*o* boundary.

Finally, consider the area surrounding the boundary between buying l and buying h. Around this boundary, both prices are lower than q_h and thus $\Delta_q > \Delta_p$. Focusing predicts that agents will overweight quality, shifting preferences toward h and leading to an upward shift in the *l*-*h* boundary. Relative thinking predicts the opposite: increased price sensitivity that favors l and causes a downward shift in the *l*-*h* boundary.

Figure 2 highlights the source of identification for γ: the observed choice boundaries identify its sign and magnitude. More formally, consider an agent with some γ_1 making choices in the area surrounding the *l*-*o* boundary. The threshold prices for which this agent is indifferent between l and o is defined by the equation $p_l = q_l \left(q_h/p_h\right)^{\gamma_1}$. Using this structure, it is possible to use observed choices at different prices to map out the indifference boundary and hence calculate the value of γ_1. The same intuition extends to the *h*-*o* and *l*-*h* boundaries.

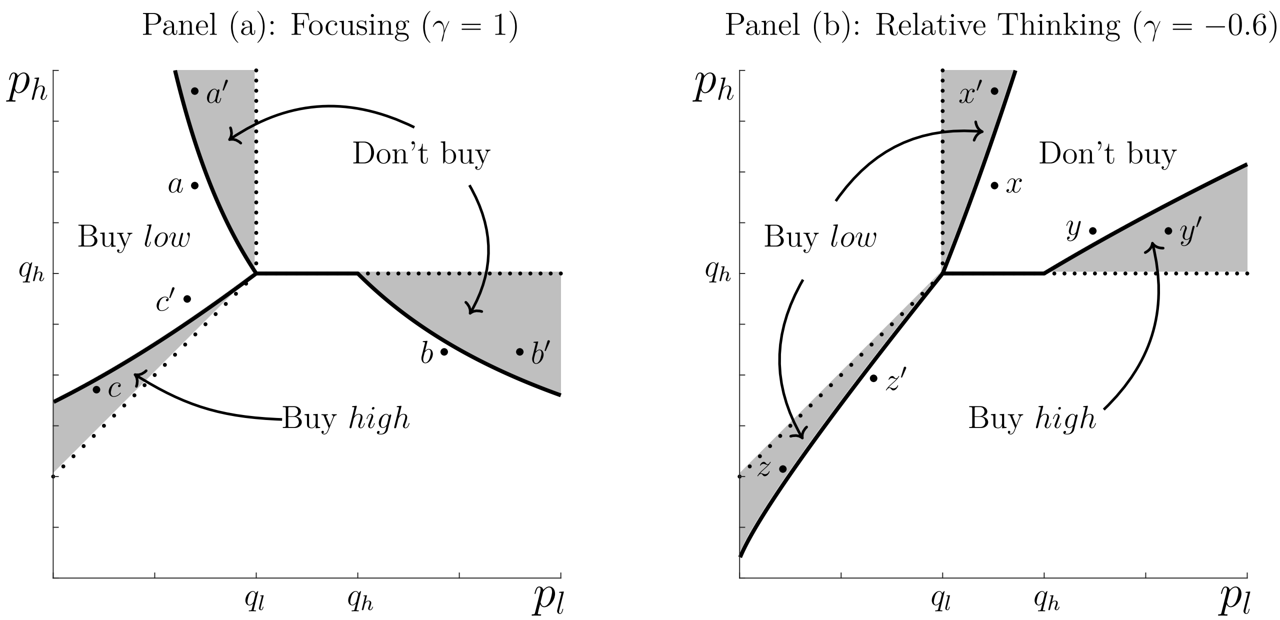

Figure 2: Optimal choices for focusing (left panel) and relative-thinking (right panel) agents given a choice between a high- and low-quality variant of a product along with the option to not buy. The subjective values of the high- and low-quality variants are fixed and denoted by q_h and q_l. The weight on attribute $x \in \{q, p\}$ is $(\Delta_x)^\gamma$ where $\Delta_q = q_h$ and $\Delta_p = \max\{p_h, p_l\}$. The left panel depicts the indifference set for $\gamma = 1$ and the right panel depicts the indifference set for $\gamma = -0.6$. The dotted lines denote the surplus-maximizing indifference set ($\gamma = 0$). The highlighted points are examples of choice reversals that are inconsistent with surplus maximization.

The experiment will create variation around all three boundaries, and my main estimation of γ will use all the data. However, in principle, γ could be estimated from any one boundary. As a validation exercise, I also estimate γ separately using data around each boundary and check whether I get similar estimates.

1.3 Nonparametric Identification

The identification argument in Section 1.2 generalizes beyond the parametric form A4. The following proposition establishes identification of the range-weighting parameter γ with ideal data for choice sets of the form $\mathcal{C}(p_h, p_l)$. Ideal data in this context consist of observing choices at every price pair $(p_h, p_l) \in \mathbb{R}^2_+$. Let $j(p_h, p_l)$ denote the observed choice correspondence. Let $j^*(p_h, p_l|\gamma) \equiv \arg\max_j \left[g(\Delta_q; \gamma)\, q_j - g(\Delta_p; \gamma)\, p_j\right]$ define the model-implied choice correspondence, which maps prices to choices for a given γ. The data set contains the observed choice $j(p_h, p_l)$ at all price pairs $(p_h, p_l) \in \mathbb{R}^2_+$.

Proposition 1: Suppose that A3 holds. Then for choice set $\mathcal{C}(p_h, p_l)$, there exists either

i. No γ such that $j^*(p_h, p_l|\gamma) = j(p_h, p_l)$ for all $(p_h, p_l) \in \mathbb{R}^2_+$, or

ii. A unique γ such that $j^*(p_h, p_l|\gamma) = j(p_h, p_l)$ for all $(p_h, p_l) \in \mathbb{R}^2_+$.

Proposition 1 states that the parameter γ can be identified for any family of functions admitting a single-index representation, subject to mild regularity conditions.[4] Intuitively, any feasible γ maps out unique indifference boundaries in the $(p_h, p_l) \in \mathbb{R}^2_+$ space. Observing choices for every possible price pair maps out the boundaries generated by γ. Qualitatively, these boundaries are similar to those depicted in Figures 2 and 3: they shift smoothly in response to changes in γ. Therefore, each partition corresponds to a distinct γ, and so revealing these boundaries is sufficient to identify γ. The proof of Proposition 1 defines three mutually exclusive regions that contain the *l*-*o*, *h*-*o*, and *l*-*h* indifference boundaries. Within each of these regions, either of the two relevant choices can be rationalized by some $\gamma \in (\underline{\gamma}, \overline{\gamma})$. This formalizes the intuition that there are three distinct sources of identification for γ: one for each indifference boundary.

1.4 Comparative-Statics Predictions

In this section, I derive the comparative-statics predictions that the experiment tests. In the previous section, I assumed that there was a perfect mapping from utilities to choice. In practice, choices are noisy which can lead to random deviations from the model predictions. To account for such errors, I assume that choice is based on utility plus an additive i.i.d. error term that captures choice noise. This gives rise to choice probabilities and my comparative-static predictions focus on how those probabilities respond to changes in prices under each model.

First, consider what random utility maximization predicts for choice sets of the form $\mathcal{C}(p_h, p_l)$. Under this approach, agents evaluate each option $\mathcal{U}_j = U_j + \varepsilon_j$ and choose $j^* \equiv \arg\max_j \mathcal{U}_j$. Let $\widehat{\varepsilon}_{jk} \equiv \varepsilon_j - \varepsilon_k$ denote the error difference between options j and k. The only restriction I place on this error difference is that the joint distribution of error differences is

[4] All proofs can be found in Appendix A.

strictly positive at all values; in other words, that there is always a non-zero probability of choosing each option. With minimal assumptions on U_j and ε_j, random utility maximization has clear testable predictions.

Proposition 2: Suppose A1 holds, the choice set is $\mathcal{C}(p_h, p_l)$ and choice is determined by j^*. Then, the probability of choosing h or l is strictly decreasing in the prices of h and l.

Proposition 2 states an obvious prediction of utility maximization: agents are less likely to buy h or l when prices increase. Crucially, range-dependent attribute weighting suggests that there are certain price regions in which this prediction does not hold. Around each of the indifference boundaries in Figure 2, one of three options serves as a "decoy": this option is never chosen, yet it affects preferences for the two nondecoy options by altering the relative weights on quality versus price. Framed in this way, there are three types of choice sets contained in $\mathcal{C}(p_h, p_l)$ that are of interest: h-decoy, l-decoy, and o-decoy.[5] Prices from these decoy regions provide a test of utility maximization and allow for simple comparative-statics tests of whether γ is positive, negative, or zero.

Prices around the l-o boundary imply that h is the decoy option. While h has superior quality, agents will not purchase it due to its high price. However, increasing the price of h in this region can cause demand to shift toward either l or o depending on the sign of γ. Intuitively, because p_h determines the price range, changes in p_h alter the relative weight on price. For example, consider points a and a' in Figure 2 panel (a). At point a, l is preferred to not buying. At point a', the higher price of h expands the price range while p_l remains unchanged. According to focusing, this leads to greater price sensitivity and a choice reversal from buying l to not buying. Conversely, relative thinking predicts that the higher p_h can shift demand toward buying l. Intuitively, a wider price range reduces price sensitivity, boosting the appeal of l relative to not buying. For example, moving from point x to x' in panel (b) leads to a choice reversal from not buying to buying l.

Prices around the h-o boundary imply that l is the decoy option. This is a more traditional decoy situation because h asymmetrically dominates l. Once again, the price range exceeds the quality range on l-decoy decisions. As a result, focusing predicts that demand can shift

[5] The proof of Proposition 1 provides a formal definition of these three regions.

from buying h to not buying (for example, b to b') and relative thinking predicts demand shifts from not buying to buying h (for example, y to y').

Prices from around the l-h boundary lead to the most novel type of decoy situations. Here, the prices of both l and h are relatively low, and hence one of these two options is always chosen. Not buying serves as a decoy because it expands the quality range by more than the price range, but it is never chosen. As a result, increasing the price level brings the attribute ranges, and hence their relative weights, closer to parity. Therefore, range-dependent attribute weighting predicts that both relative prices and the absolute price level matter when deciding between h and l. Specifically, for a fixed price difference, focusing predicts that higher prices can cause demand to shift toward l (for example, point c to c'), while relative thinking predicts that demand can shift toward h (for example, point z to z').

The predictions outlined above do not account for choice noise. In practice, random errors in evaluation will imply that the decoy option is sometimes chosen. An implication of this behavior is that choice probabilities may not be monotonic in the utility difference between the nondecoy options due to substitution to and from the decoy option. For example, suppose that probability of choosing l is increasing in the price of h in the h-decoy region. This is consistent with relative thinking but could also be consistent with focusing if there is enough substitution from h to l. However, focusing would also predict that the probability of choosing o is increasing in the price of h, while relative thinking predicts the opposite. As a result, the full pattern of substitution needs to be taken into account when testing for focusing versus relative thinking. Formally, suppose that range-weighting agents evaluate each option j as $\mathcal{V}_j = V_j + \epsilon_j$, and choose $j^*_\gamma \equiv \arg\max_j \mathcal{V}_j$. The following proposition establishes how choice probabilities respond to changes in prices for different γ values.

Proposition 3: Suppose A3 holds, the choice set is $\mathcal{C}(p_h, p_l)$, and choice is determined by j^*_γ.

(a) If the price of h increases in the h-decoy region, then the probability of choosing:

  (i) l is increasing, h is decreasing, and o is increasing if $\gamma = 0$

  (ii) l is increasing or decreasing, h is decreasing, and o is increasing if $\gamma > 0$

  (iii) l is increasing, h is decreasing, and o is increasing or decreasing if $\gamma < 0$.

(b) If the price of l increases in the l-decoy region, then the probability of choosing:

  (i) l is decreasing, h is increasing, and o is increasing if $\gamma = 0$

(ii) l is decreasing, h is increasing or decreasing, and o is increasing if $\gamma > 0$

(iii) l is decreasing, h is increasing, and o is increasing or decreasing if $\gamma < 0$

(c) If the price of h increases in the o-decoy region for a fixed $p_h - p_l$, then the probability of choosing:

(i) l is decreasing, h is decreasing, and o is increasing if $\gamma = 0$

(ii) l is increasing or decreasing, h is decreasing, and o is increasing if $\gamma > 0$

(iii) l is decreasing, h is increasing or decreasing, and o is increasing if $\gamma < 0$

Proposition 3 provides a guide for mapping empirical choice probabilities to an implied γ. In each price region, the three models make distinguishing predictions for how the likelihood of choosing each option responds price increases. These comparative statics are main non-parametric tests explored in this paper. Crucially, they show that it is possible to distinguish the predictions of surplus maximization, focusing, and relative thinking using only data on prices and choices.

1.5 From Theory to Design

The experiment is designed to generate ideal variation for identifying range-based attribute weighting. I focus on the context in which participants are asked to choose between a high- and low-quality variant of a product along with the option of not buying either. It is possible to identify γ in this common economic environment, with the practical advantage of requiring only two known qualities per product.

Mapping the theoretical predictions to actual choice settings requires further assumptions. First, I assume that each option is summarized by two attributes, price and a generic measure of quality that can be expressed in monetary terms. The meaning of quality will differ across products and is not directly comparable: for example, the “quality” of chocolate will differ from the “quality” of a television. In practice, some measures of quality will be easier to put on a scale than others; it might be harder to place two options varying in brand or functionality on a quality ladder than two options varying in quantity or duration. In the experiment, I use a wide range of products to enhance the generalizability of the results. Section 2.2 provides further details about the products used in the experiment.

Second, in the theoretical framework I assume that not buying is treated like any other option in the choice set and that it has zero quality. In the experiment, I also treat not buying like any other option in the choice set: it is given equal prominence in the display and is labeled with a price tag of $0.00. In real markets, not buying might not feature so prominently in consumers' choice sets. If participants place a nonzero quality value on not buying for some options, then the willingness-to-pay measures that I elicit can simply be reinterpreted as the difference in quality between buying and not buying.

The theoretical predictions are based on observing choices at all possible prices. In reality, the number of choices I can elicit from participants is limited by practical considerations. The identification argument in Section 1.2 suggests an efficient way to sample prices for the parametric form $(\Delta)^{\gamma}$. For example, suppose the experimenter wanted to detect some $\gamma \in (0, 1)$. Then, sampling prices from the shaded areas in panel (a) of Figure 2 is sufficient to identify any $\gamma \in (0, 1)$. Similarly, sampling prices from the shaded areas in panel (b) of Figure 2 is sufficient to identify any $\gamma \in (-0.6, 0)$. Intuitively, the experimenter only needs to sample prices from regions that contain the indifference boundaries.

Figure 3 depicts seven indifference boundaries generated A4 for the set of γ values $\{2, 1, 1/2, 0, -1/3, -2/3, -1\}$. Each γ value corresponds to a unique indifference boundary in each of the *l-o*, *h-o*, and *l-h* regions. This generates six price zones around each indifference boundary from which I draw experimental prices. Observing choice patterns across these zones is sufficient to identify any $\gamma \in (-1, 2)$. In the experimental design, I generate prices for each subject by randomly drawing one (p_h, p_l) from each of these 18 price zones.

Defining the experimental price zones in Figure 3 requires knowledge of the individual-specific qualities, q_h and q_l. One approach to measuring quality is to vary the scale of quality dimension and estimate the shape of the entire quality ladder. An advantage of this method is that it permits richer experimental variation in quality. However, this method requires many observations per product and additional structural assumptions. My approach to identification treats quality as fixed and leverages price variation. Furthermore, Section 1.2 shows that for the range-weighting model, reservation values reveal quality when individuals choose whether or not to buy a product in isolation. I use this result to obtain direct proxies for each individual's quality for both a high- and a low-quality variant of multiple products. Specifically, I implement a two-stage experimental design: an online survey designed to elicit proxies for quality and an in-person choice task in which prices are calibrated using the first stage responses.[6] This approach to measuring quality has the practical advantage of requiring only two questions per product and allows me to consider a broader range of products.

One drawback of eliciting a single measure of quality per product variant is measurement error. Recent work has highlighted that using multiple, independent measures can help to reduce this error (Gillen, Snowberg, and Yariv, 2019). Building on this intuition, I elicit two measures of quality: one prior to the choice task and one after. I also use two different elicitation techniques: free response and a multiple price list. While both approaches have some well-publicized shortcomings (e.g. Cason and Plott (2014) and Andersen et al. (2006)), both measures should provide some signal value about underlying quality. By obtaining two signals of quality using different elicitation methods, I can combine them optimally in the structural analysis and perform additional robustness tests. Section 2 describes the full details of the design.

2 Experimental Design

This section describes the implementation of my laboratory experiment. Appendix B contains all instructions to participants and additional screenshots of the experiment. Online surveys took place on the Qualtrics platform. The main experimental interface was programmed in Matlab and Psychtoolbox. In-person sessions took place at Cornell's Lab for Experimental Economics and Decision Research (LEEDR) in nine sessions spread over five days in February 2018.

2.1 Method and Implementation

I recruited 190 non-students for the experiment from an online participant pool administered by LEEDR. Participants enrolled in this system are non-faculty Cornell staff and

[6] A key assumption of range-weighting models is that agents narrowly frame each choice. If participants instead view decisions as part of a broader choice set, then reservation values may be biased. For example, if participants treat the Becker, DeGroot, and Marschak (1964) (BDM) mechanism as a lottery and in the absence of an explicit upper bound on price participants assume some large $\bar{p}$, then my quality proxies may not reflect true quality. To the extent that experimental prices were imprecise due to inaccurate quality proxies, my estimates will be biased towards a null effect.

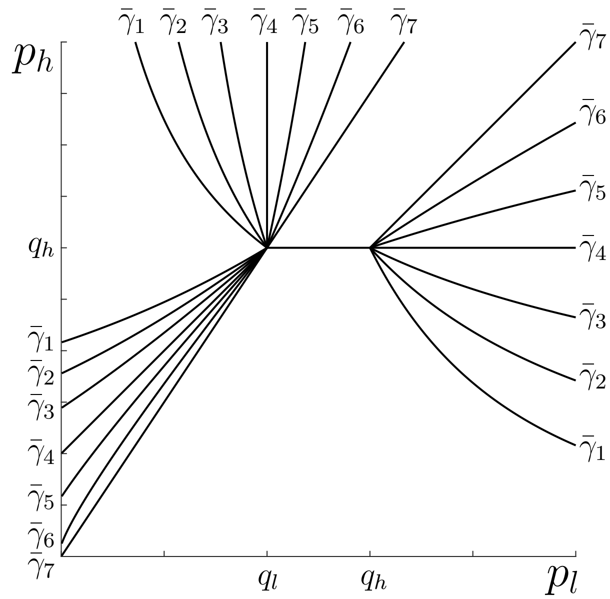

Figure 3: Depiction of the zones from which experimental prices were drawn. The solid black lines denote indifference boundaries for $\{\bar{\gamma}_1, \bar{\gamma}_2, \bar{\gamma}_3, \bar{\gamma}_4, \bar{\gamma}_5, \bar{\gamma}_6, \bar{\gamma}_7\} = \{2, 1, 1/2, 0, -1/3, -2/3, -1\}$ and are constructed for the attribute weighting function $(\Delta)^\gamma$. Agents are modeled as choosing between a high- and low-quality variant of a product along with the option to not buy. The subjective values of the high- and low-quality variants are fixed and denoted by q_h and q_l.

non-affiliated local residents.[7] The experiment consisted of two parts: an online valuation task and an in-person choice task.

Stage 1: The Online Valuation Task

The valuation task consisted of decisions of the following form:

"Please enter the amount that makes you indifferent between the following two options.

Option A: Do not purchase the product.

Option B: Spend $[ ] and receive [product description]."

The product was depicted below this text and participants could choose to reveal detailed product information by clicking a link. Each participant completed 24 decisions like this (referred to hereafter as trials)—one for a "high"-quality variety (h) and one for a "low"-quality variety (l) for each of 12 products (see Section 2.2 for product details). The trials for the h and l varieties of each product appeared back-to-back in random order. Participants

[7]One advantage of this non-student sample is that it is more diverse compared to the student participant pool. This allows for richer modeling of individual differences in range-dependent attribute weighting.

could enter any positive amount they wished and could state a higher valuation for whichever of the two varieties they preferred. Upon completion of the trials for a given product, a confirmation screen displayed the stated valuation for each variety side-by-side and asked participants to confirm their responses. The order in which each of the 12 products appeared was also randomized.

All participants received a flat \$20 payment for taking part in the study and had the opportunity to win additional bonuses. To incentivize responses, participants had an approximately one-in-five chance of winning an additional cash payment of \$80 during the second stage (see details below).[8] If participants won this additional \$80, there was a 20% chance that one of their choices from the first stage would be implemented for real using the BDM mechanism.[9] An appealing feature of this bonus-payment structure is that it incentivizes participants to treat each decision independently. The independence of each trial was repeatedly emphasized in the instructions.

Participants were emailed a link to the valuation task seven days before the in-person choice task and asked to complete it in one sitting. The deadline for completing the online survey was 72 hours after the link was received. This meant there were at least 96 hours between completion of the first stage and the beginning of the second stage. This gap reduced the possibility that subjects anchored on their first-stage valuations when making choices during the second stage.[10]

I imposed certain eligibility criteria on the first-stage reservation values. First, reservation values for the two varieties of the product had to differ. Second, valuations had to be nontrivial to allow scope for price variation. Third, reservation values could not be so high that the participation payment could not cover the purchase cost. Finally, blatant nonmonotonicities, such as participants stating higher valuations for l than h, were removed. To

[8] The average cash payment upon completion was \$34 and the average value of goods received was \$6 (15 individuals received products with an average value of \$56.05).

[9] The BDM mechanism was executed as follows. A price, p^*, was drawn at random from a uniform distribution over the support $(0, p_{max})$, where p_{max} was set to be the total payment (e.g. \$20 participation fee + the \$80 bonus). If willingness-to-pay was below the randomly drawn price ($WTP < p^*$), the product was not purchased. If willingness-to-pay was above or equal to the randomly drawn price ($WTP \geqslant p^*$), the participant received the product and had p^* deducted from their payment.

[10] Practically, it also ensured that all participants had completed the first stage before anyone had completed the second stage. As the first stage valuations were taken as inputs to the second stage, it was important to ensure that no information about the choice task was revealed to anyone until after all participants had completed the valuation task; otherwise participants might have entered false valuations in an attempt to manipulate the prices they saw during the second stage.

ensure these four conditions were satisfied, participants had to value the high-quality variant strictly more than the low-quality variant, and their valuations had to lie within the interval $[\$4, \$100]$ for at least nine of the products. If fewer than nine products satisfied these criteria, participants were ineligible for second stage. If more than nine product valuations met the eligibility criteria, any products valued at the upper limit of $100 were dropped to enhance the scope for price variation in the second stage. If the final set of eligible products was ten or more, then nine were selected at random. Of the 190 participants who completed the valuation task, 26 were ineligible for the second stage. An additional 14 participants did not show up or cancelled, leaving a final sample size of 150. The final sample was 72.7% female, 81.3% white, and 54% married. The median participant was 47 years old, had a bachelor's degree, and lived in a household with annual income between $75,000 and $99,999.

Stage 2: The Choice Task

At the in-person lab session, participants made a series of choices from bundles containing two varieties of the same product with the option to not purchase either. In each trial, participants encountered one of nine products from the first stage. Participants completed a total of 18 trials (two per product), presented in two blocks of nine (one trial per product). Trials in each block were randomized subject to the proviso that the last good in block 1 was not the first good of block 2. The location of each option was random in each trial.

Figure 4 depicts a typical trial. Each option was displayed onscreen along with a price tag. The option of not buying was included explicitly; it was represented by a red circle with a line through it and a price tag labaled $0.00. The onscreen text instructed participants to consider the three options for the first ten seconds. Once this initial viewing time elapsed, additional text appeared onscreen asking participants to choose their preferred option. Participants responded by pressing one of three keys labeled "A", "B", or "C" on the keyboard in front of them. They could also reveal detailed product information by pressing (and holding) one of three "INFO" buttons on the keyboard. The average time spent completing each trial was 18 seconds.

The key experimental manipulation in each trial was the prices of the high- and low-quality variants. In each trial, the prices of h and l were drawn from one of the 18 subregions

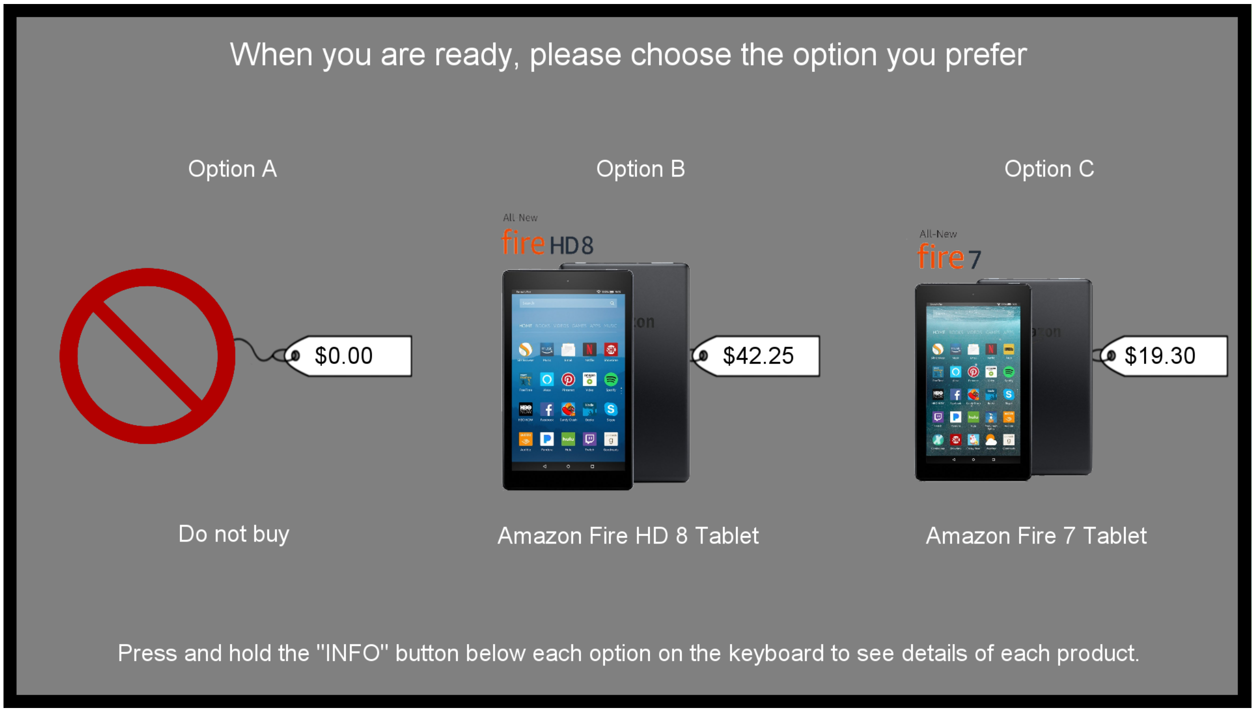

Figure 4: Screenshot of a second-stage choice task. Participants respond by pressing one of three keys labeled "A", "B", and "C" on the keyboard in front of them. Detailed product information is displayed by pressing (and holding) one of three "INFO" keys. This example trial is generated for an individual who valued the Fire 8 tablet at $59.99 and the Fire 7 Tablet at $39.99 in the first stage.

visualized in Figure 3.[11] These subregions were chosen to ensure that there was sufficiently granular price variation for estimation while not fatiguing participants with too many trials.

I imposed two further restrictions on prices. First, I set prices so that the decoy option in each region had the smallest surplus by a margin of at least 25%. In practice, the minimum price of h and l was set to $1.25q_h$ in the h-decoy and l-decoy price regions, respectively. For prices in the o-decoy price region, the maximum price of l was $0.75q_l$. Second, I imposed a universal maximum price of $\max\{2q_h, \$100\}$ and a universal minimum price of $0.50.

Participants had the opportunity to win an $80 bonus payment after each decision. They chose a number between one and 144, which was then highlighted in green on one of 144 red balls onscreen. An animation then highlighted one of the balls in yellow every 0.01 seconds and participants could stop the animation by pressing the space key (see Appendix B for screenshots of this animation).[12] If the animation stopped on their chosen number, they

[11]Further details of the price generation procedure can be found in Appendix B.

[12]Typically, it takes humans at least 0.2 seconds to react to a stimulus (Thorpe et al., 1996). As a result,

received the bonus payment and their previous choice was implemented for real; in other words, they would purchase the chosen option at the posted price.[13] Participants could win multiple bonuses and spent an average of 13.6 seconds completing each ball draw.

The motivation for this incentive structure was twofold. The first was to incentivize participants to respond as if each decision were real; making each choice *potentially* real was the most feasible option given the relatively large stakes involved. The second motive was to reduce any potential contamination of the choice set across trials by providing psychological distance between each choice. Therefore, the incentive implementation was designed to be distracting and somewhat entertaining. To encourage participants to treat each decision independently, the following text was displayed on completion of the incentive animation: "your previous choice is now final and will have no bearing on future decisions."

Once participants had completed all 18 choice trials, they faced a valuation task similar to that in stage 1 for the nine products used in the second stage. The purpose of this task was to obtain a second estimate of quality to aid estimation and allow for robustness checks. The procedure was the same as the first stage, but with the following modifications. Rather than inputting a value directly, participants decided whether or not to purchase the displayed product at the posted price. The price started at \$0 and rose in increments of \$5, up to \$100. On average, participants spent 29.5 seconds making choices for each product variety. The average price at the switching point was taken as the reservation value for that product. If more than one crossing point was indicated, the non-monotonicity was explained to participants and they repeated their choices for that product variety.

At the end of the second stage, participants had a further opportunity to win a bonus of \$80 and have one of their valuation trials (24 online + 18 in person) implemented for real. Participants could choose nine numbers from one to 144. Then, the random-ball-draw animation was implemented as before. If the animation stopped on one of the chosen numbers, the participant received a bonus of \$80. Further, one of their valuation trials from either the online survey or in-person trials was chosen at random and implemented for real using the BDM procedure.

individuals could not affect the probability of winning. Indeed, the realized winning rate was close to the theoretical rate of one in five (25 out of 150 participants won this bonus once and three won it twice).

[13]21 participants won a bonus during the choice task and went on to make subsequent decisions. In total, these participants made 200 decisions after receiving a bonus. All results are robust to excluding these observations from the analysis.

Participants proceeded through the task at their own pace and all instructions appeared onscreen. Once the task was completed, participants were given a brief post-study questionnaire to complete before receiving their payments. All products were delivered electronically or mailed to participants.

2.2 Products

The products used in the experiment were chosen to achieve several objectives. First, reservation values needed to be non-trivial. To achieve this, the menu of products had an average retail value of approximately $60 and was chosen to be widely appealing. Furthermore, the exact products participants saw were tailored to their tastes: before completing any trials, each participant selected 12 products that they would most like to purchase from a list of 20. The chosen products were then used throughout the remainder of the experiment.

Second, the experiment featured many products to prevent potential contamination of the choice sets due to repeated encounters with the same product. Nine out of the 12 products chosen by participants in stage 1 appeared in stage 2. Participants never saw the same product back-to-back and made no more than two choices per product.

Third, the products provide a clear mapping from the theoretical framework to the experimental design. Products conformed to a natural quality ladder, with each product differentiated by one of four broad features: quantity (more vs. less), duration (longer vs. shorter), functionality (more vs. less), and brand (known high quality vs. private label). Each product had two vertically differentiated variants. Examples of these product categories include quantity of chocolate truffles, duration of a wine club membership, a premium versus basic streaming device, and branded versus private label reusable batteries. The complete list of products and variants used in the experiment can be found in Appendix B.

3 Nonparametric Evidence

First, I assess whether the aggregate demand shares are consistent with random utility maximization. Proposition 2 establishes that utility maximization implies demand for h or l is decreasing in the prices of h and l. However, range-dependent attribute weighting suggests that this prediction may not hold for the price of the decoy option in the associated price region. To test this prediction, I estimate the probability of choosing h or l as function of the prices of h and l.

Table 1: Testing Utility Maximization

	(1)	(2)
Decoy Region:	h	l
Dependent Variable:	Buy *low* or *high*	Buy *low* or *high*
Price of h	0.28	−0.83
	(0.10)	(0.11)
Price of l	−0.60	0.61
	(0.15)	(0.10)
Mean of DV	59.1	59.3
Individuals	150	150
Observations	900	900

Average marginal effects derived from logistic regression estimates. The choice set consists of a high-quality (h) and low-quality (l) variant of a product, along with the option to not buy. The decoy option was priced such that it is clearly inferior and it alters the attribute ranges within the choice set. The specification includes participant demographics (age, gender, education, marital status and ethnicity) and round fixed effects. Individual cluster-robust standard errors in parentheses. All numbers reported in percentages.

Columns (1) and (2) of Table 1 present the estimates from the h- and l-decoy regions. The estimates are inconsistent with utility maximization in both regions: higher decoy prices lead to an increase in buying. A \$1 increase in the price of the h-decoy option made participants 0.28 percentage points more likely to buy h or l, while a \$1 increase in the price of the l-decoy option made participants 0.61 percentage points more likely to buy h or l.

The main hypothesis I assess is whether the data are consistent with focusing or relative thinking. My identification argument relies on observing shifts in choice probabilities due to changes in the prices of decoy options. Table 2 presents the aggregate demand shares for each experimental price region. In all three experimental price regions, participants saw an equal number of prices above and below their stated indifference values for the two nondecoy options. If the first-stage reservation values are unbiased proxies for quality, then surplus maximization predicts equal demand shares for these two options. In contrast, range-dependent attribute weighting predicts higher demand for one of the two nondecoy options, with focusing and relative thinking making opposite predictions.

Table 2: Demand Shares by Experimental Price Region

Fraction Choosing:	(1) *high* (h)	(2) *low* (l)	(3) *don't buy* (o)
***h*-decoy region**	10.9%	48.2%	40.9%
	H$_0$: (2) = (3) [$p < 0.01$]		
***l*-decoy region**	57.7%	1.7%	40.7%
	H$_0$: (1) = (3) [$p < 0.001$]		
***o*-decoy region**	36.7%	49.1%	14.2%
	H$_0$: (1) = (2) [$p < 0.001$]		

Aggregate demand shares for each option across the three experimental price regions. The price of the decoy option was always above the participant's stated willingness-to-pay. For the two nondecoy options, participants saw an equal number of prices above and below their stated indifference values. In all three regions, I test the null hypothesis that the demand shares of the two nondecoy options are equal.

In the h-decoy region, participants were 7.3% more likely to choose l over not buying ($p < 0.01$). This is consistent with a rightward shift in the indifference boundary as predicted by relative thinking and depicted in Figure 2 panel (b). In the l-decoy region, the fraction of participants choosing h was 17.0% higher than the fraction choosing to not buy ($p < 0.001$). This implies an upward shift in the indifference boundary in this region consistent with the prediction of relative thinking. Finally, in the o-decoy region participants preferred l over h by a margin of 12.4% ($p < 0.001$). This implies a downward shift in the indifference boundary, which is again consistent with relative thinking.

Participants sometimes chose the decoy option in each region, with some differences across regions. The pattern of decoy choices is consistent with choice noise. Participants were least likely to choose the l decoy, which had the greatest surplus difference relative to the next-best option. Participants were most likely to choose the o decoy, which had the smallest absolute surplus difference compared to the next-best option. Moreover, participants whose first- and second-stage valuations were more highly correlated were less likely to choose the decoy option.

To formally test for range dependence, I assess comparative-statics predictions derived in Section 1.4. Columns (i), (ii), and (iii) of Table 3 summarize the predictions stated in

Proposition 3 for surplus maximization, focusing, and relative thinking, respectively. This analysis does not rely on the first-stage quality perceptions elicited in the experiment. To the extent that experimental prices were miscalibrated due to inaccurate quality proxies, the estimates will be biased towards finding a null effect.

Table 3: Change in Choice Probabilities in Response to Price Increases

	(i) Surplus Maximization $\gamma = 0$	(ii) Focusing $\gamma > 0$	(iii) Relative Thinking $\gamma < 0$	(iv) Data
		(a) $\uparrow$ $\boldsymbol{p_h}$ in the $\boldsymbol{h}$-decoy region		
Buy *high*	↓	↓	↓	↓
Buy *low*	↑	↑ or ↓	↑	↑
Don't buy	↑	↑	↑ or ↓	↓
		(b) $\uparrow$ $\boldsymbol{p_l}$ in the $\boldsymbol{l}$-decoy region		
Buy *high*	↑	↑ or ↓	↑	↑
Buy *low*	↓	↓	↓	↓†
Don't buy	↑	↑	↑ or ↓	↓
		(c) $\uparrow$ $\boldsymbol{p_h}$ in the $\boldsymbol{o}$-decoy region*		
Buy *high*	↓	↓	↑ or ↓	↑
Buy *low*	↓	↑ or ↓	↓	↓
Don't buy	↑	↑	↑	↑†

*For a fixed $p_h - p_l$. †not statistically significant at conventional levels. Summary of the predictions of surplus maximization, focusing, and relative thinking, along with the choice probability estimates from Table 4. The choice set consists of a high- and low-quality variant of a product, along with the option to not buy. The decoy option is priced such that it is clearly inferior and it alters the attribute ranges within the choice set. The predictions in panels (i), (ii), and (iii) are stated in Proposition 3 in Section 1.4. Panel IV summarizes the direction of the estimated coefficients in Table 4.

Table 3 provides a guide for mapping choice probability estimates to a value of γ. The key to identifying range weighting is to focus on deviations from surplus maximization. Panels (a), (b), and (c) summarize how choice probabilities respond to expansions in the price range for surplus maximization, focusing, and relative thinking. According to focusing, expanding the price range makes individuals more price sensitive. This implies that individuals will become less likely to buy l in the h-decoy region, less likely to h in the l-decoy region, and more likely to buy l in the o-decoy region. Conversely, relative thinking assumes that wider price ranges decrease price sensitivity. This implies that individuals will become less likely to not buy in the h- and l-decoy regions, and more likely to h in the o-decoy region.

To test these predictions, I estimate the probability of choosing h, l, and o as a function of the prices of h and l using a logistic regression for each of the three decoy choice sets. Panel (a) of Table 4 presents the results for the h-decoy choice sets. The estimates are consistent with the law of demand: participants were less likely to buy l or h when its own price was higher, as predicted by surplus maximization, focusing, and relative thinking. However, higher prices of the decoy option h led to an increase in the likelihood of choosing l and a decrease in the likelihood of not buying. Consistent with relative thinking, a \$1 increase in the price of h increased the probability of buying l by 0.44 percentage points and decreased in the probability not buying by 0.28 percentage points.

Panel (b) presents the estimates for the l-decoy choice sets. The probability of choosing h is again decreasing in its own price but increasing in the price of the decoy option, l: a \$1 increase in the price of l increased the probability of buying h by 0.60 percentage points. Furthermore, the probability of not buying is decreasing in the price of the decoy option: A \$1 increase in the price of l reduces the likelihood of not buying by 0.61 percentage points. This pattern of results is again consistent with relative thinking, but inconsistent with focusing and surplus maximization.

To assess the impact of parallel price increases in the o-decoy region, I estimate the likelihood of choosing each option as a function of both the price difference between h and l and the absolute price level of h. The results, presented in panel (c), show that the absolute price level matters: for a fixed price difference, higher prices of h are associated with increased demand for h. This result is only possible under relative thinking, and is not permitted under focusing or surplus maximization.

Panel IV of Table 3 summarizes the evidence from Table 4. Across all three price regions, expanding the price range through decoy options increases the probability of buying the highest quality nondecoy option. The overall pattern of results is consistent with relative thinking, which predicts that wider price ranges reduce price sensitivity. In all cases in which surplus maximization, focusing, and relative thinking make distinguishing predictions, the data support relative thinking.

Table 4: Testing Focusing versus Relative Thinking

	(1)	(2)	(3)
Dependent Variable:	Buy *high*	Buy *low*	Don't Buy
	Panel (a): *h*-decoy region		
Price of h	−0.16	0.44	−0.28
	(0.07)	(0.09)	(0.10)
Price of l	0.42	−1.11	0.60
	(0.09)	(0.14)	(0.15)
	Panel (b): *l*-decoy region		
Price of h	−0.80	−0.01	0.83
	(0.11)	(0.03)	(0.11)
Price of l	0.60	−0.01	−0.61
	(0.10)	(0.03)	(0.10)
	Panel (c): *o*-decoy region		
Price of h	0.52	−0.74	0.22
	(0.21)	(0.24)	(0.15)
Price Difference	−1.48	1.75	−0.35
(h minus l)	(0.30)	(0.32)	(0.20)
Individuals	150	150	150
Observations	900	900	900

Average marginal effects derived from logistic regression estimates. The choice set consists of a high-quality (h) and low-quality (l) variant of a product, along with the option to not buy. The decoy option was priced such that it is clearly inferior and it alters the attribute ranges within the choice set. The specification includes participant demographics (age, gender, education, marital status and ethnicity) and round fixed effects. Demographic and round fixed are excluded in specification (2) for the l-decoy regressions due to the lack of variation in the outcome variable. Individual cluster-robust standard errors in parentheses. All numbers reported in percentages.

3.1 Individual Heterogeneity

Evidence of relative thinking in the aggregate may mask substantial individual heterogeneity in range-dependent attribute weighting. This is particularly relevant in my experimental context because relative thinking and focusing make opposite predictions. It is possible that many participants made choices consistent with focusing despite aggregate demand patterns consistent with relative thinking.

To investigate individual heterogeneity in range-dependent attribute weighting, I measure how each participant's choices align with the predictions of focusing and relative thinking. The price variation that permits identification of γ in the aggregate data also allows me to classify each participant as a focuser or relative thinker. In each trial, there is always a choice that is consistent with focusing, relative thinking, and surplus maximization. For example, when l is priced below a participant's reservation value in the h-decoy region, choosing l is consistent with all three models provided γ is not too large. However, there is also a choice that can falsify one of the range models and surplus maximization: for example, choosing o is inconsistent with relative thinking and surplus maximization in the previous example. By the same logic, when l is priced above a participant's reservation value in the h-decoy region, choosing o or l is consistent with relative thinking but only choosing o is consistent with focusing.

For each participant, I score how many of their 18 experimental choices are consistent with focusing or with relative thinking. Based on these scores, 58.7% of participants are most consistent with relative thinking, 32.7% are most consistent with focusing, and 8.7% are equally consistent with both models. The average consistency scores for the relative thinkers, focusers, and equally consistent types were 15.0, 14.0, and 13.7, respectively. As a benchmark, a participant choosing at random would make nine choices consistent with both focusing and relative thinking in expectation. To test whether these scores are statistically different from random choice, I compute the random-choice null distribution of consistency scores. Noting that the consistency score for each participant is simply the sum of two binomial distributions under this null, it follows that a score of 12 or more is inconsistent with random choice at the conventional 5% significance threshold. Using this cutoff value, I can reject the random-choice benchmark for 97% of relative thinkers, 94% of focusers, and 92% the equally consistent types.

I also score each participant's choices for consistency with surplus maximization. On average, participants made 10 choices that were consistent with surplus maximization. As a benchmark, a participant choosing at random would make six surplus maximizing choices. A score of nine or more is inconsistent with the randomization null at the conventional 5% significance threshold. I can reject this benchmark for 72% of participants. Overall, relative thinking improves the consistency score versus surplus maximization by at least one score for 86.7% participants.

While almost one third of participants were best classified as focusers, they also appear to make noisier decisions. First, focusers had significantly lower consistency scores on average compared to relative thinkers ($p < 0.01$). Second, the quality valuations in the first and second stage were less correlated for focusers compared to relative thinkers. The average correlation was 0.51 for focusers versus 0.63 for relative thinkers, a difference that is statistically significant from zero ($p < 0.01$). Furthermore, focusers were more likely to choose the decoy option compared to relative thinkers. On average, focusers chose the decoy option 2.1 times versus 1.3 times for relative thinkers ($p < 0.01$).

To assess whether participants are classified as focusers or relative thinkers due to noise or genuine choice-set dependence, I re-estimate the choice probabilities as a function of prices for both groups. Columns (1) to (3) of Table 5 present the results for the relative thinkers. The estimates are similar to the aggregate results: wider price ranges are associated with buying more and cause substitution to higher quality options. However, for the focusers, the estimates in Panel (b) do not support the comparative-statics predictions of focusing. In the h- and o-decoy regions, the estimated coefficients are most consistent with noisy surplus maximization. In the l-decoy region, the estimates are consistent with relative thinking. Overall, the apparent focusers do not respond to price changes in a manner consistent with focusing.

Finally, I implement a parametric approach to estimating individual heterogeneity in range-dependent attribute weighting in Appendix C.1. The results confirm that the majority of participants are relative thinkers: I estimate negative γ for around three-quarters of participants. For the remaining participants, I estimate large choice noise and imprecise γ parameters: only two participants in my sample have a γ parameter that is positive and significantly different from zero. Furthermore, the best fitting range-weighting distribution has a unimodal shape, implying a single relative-thinking type that differs in the intensity but not the direction of range weighting. Overall, the majority of participants made decisions consistent with relative thinking and there is no evidence that a nontrivial share of participants made choices consistent with focusing.

Table 5: Choice Probability Estimates by Type

	Relative Thinkers			Focusers		
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Buy *high*	Buy *low*	Don't Buy	Buy *high*	Buy *low*	Don't Buy
	***h*-decoy region**			***h*-decoy region**		
Price of h	−0.18	0.49	−0.30	−0.16	0.31	−0.15
	(0.09)	(0.13)	(0.13)	(0.14)	(0.13)	(0.17)
	***l*-decoy region**			***l*-decoy region**		
Price of l	0.46	0.03	−0.53	0.62	−0.06	−0.57
	(0.13)	(0.03)	(0.13)	(0.16)	(0.05)	(0.17)
	***o*-decoy region**			***o*-decoy region**		
Price of h	0.73	−1.02	0.35	0.22	−0.29	0.08
	(0.27)	(0.30)	(0.14)	(0.34)	(0.35)	(0.32)
Observations	528	528	528	288	288	288
Individuals	88	88	88	48	48	48

Choice-probability estimates by type classification. Participants are classified as relative thinkers or focusers based on how well their choices aligned with the theoretical predictions of each model. The numbers reported are average marginal effects derived from logistic regression estimates. The specification includes participant demographics (age, gender, education, marital status and ethnicity) and round fixed effects. Demographic and round fixed are excluded from specifications (2) and (5) for the l-decoy regressions due to the lack of variation in the outcome variable. The regressions either control for the price of l (panel a), the price of h (panel b), or the price difference between h and l (panel c). Individual cluster-robust standard errors in parentheses. All numbers reported in percentages.

4 Estimating Structural Parameters

This section provides estimates for the range-dependent attribute weighting parameter γ. This approach allows me to quantify choice-set dependence in terms of surplus foregone and to conduct other counterfactual analyses. This addresses a key motivation of this paper: does range weighting generate economically meaningful departures from surplus maximization? This approach also allows for a formal statistical test of whether relative thinking improves fit versus surplus maximization and for other robustness tests.

For individual $i = 1, ..., I$ on trial $t = 1, ..., T$, I model the overall utility of option j as

$$\mathcal{V}_{ijt} = g(\Delta_{q_t}; \gamma_i) \cdot q_{ijt} - g(\Delta_{p_t}; \gamma_i) \cdot p_{ijt} + \lambda_i \varepsilon_j \tag{1}$$

where ε_j follows a type-I extreme-value distribution and λ_i is the scale parameter for individual i. I assume that the attribute weighting function takes the parametric form A4: $g(\Delta;\gamma_i) = (\Delta)^{\gamma_i}$. The parameter of interest is γ_i, which indexes the direction and magnitude of range-based attribute weighting for individual i. Recall that $\gamma_i < 0$ indicates relative thinking, while $\gamma_i > 0$ implies focusing.[14] Conditional on γ_i and the scale parameter λ_i, specification (1) gives choice probabilities defined by the standard logit formula.

To estimate equation (1), I need to specify quality. The experimental design elicited reservation values for each good twice. I assume that the quality of each product variety, q_{ijt}, is the average of these reservation values. I explore alternative specifications of quality in Section C.4 and find that taking the average reservation value produces a relatively conservative estimate of the magnitude of γ.

In this section, I focus on estimating a homogeneous-agent model where $(\gamma_i, \lambda_i) = (\gamma, \lambda)$ for all i. In Appendix C.1, I estimate γ_i for each individual separately. Table 6 presents the parameter estimates obtained via maximum likelihood estimation. The full sample estimates are presented in column (1). A $\hat{\gamma}$ coefficient of -0.34 [95% CI: -0.41,-0.25] implies that an attribute's decision weight is inversely related to its range within the choice set, supporting the key assumption of the relative thinking model. Surplus maximization ($\gamma = 0$) lies well outside the 95% confidence interval and a likelihood-ratio test provides support for the range-weighting specification versus the null of surplus maximization ($\chi^2_1 = 126.08, p < 0.001$).

The scale parameter estimate $\hat{\lambda}$ provides an indication of the average choice noise. While it is not of direct interest, it helps to rationalize random choice deviations from the predictions of the model. The normalization of the attribute weights means that it can be interpreted roughly in surplus terms. A coefficient of 9.19 [95% CI: 8.27, 10.28] implies a standard deviation in monetized terms of $\hat{\lambda}\pi/\sqrt{6} \approx \$12$. To put this in context, the average surplus differential between the first- and second-ranked options was around \$9, while for the second- and third-ranked options, the average gap was around \$21.

Recall that in principle, γ is identified in any one of the three price regions. As a validation check, I assess the consistency of the parameter estimates across the three price

[14] To ensure that the impact of choice noise scales with the magnitude of the attribute range, I normalize the weights to sum to two. Specifically, I replace $g(\Delta_x;\gamma_i)$ by $2g(\Delta_x;\gamma_i)/(g(\Delta_q;\gamma_i) + g(\Delta_p;\gamma_i))$ for $x \in \{q, p\}$ in equation (1). Without this normalization, choice noise will matter more or less depending on the ranges of quality and price. For example, choice noise will have a larger impact in the o-decoy region due to the relatively narrow price ranges. I obtain very similar results without this normalization.

Table 6: Homogeneous Model Estimates

Trials:	(1) All	(2) h-decoy	(3) l-decoy	(4) o-decoy
$\hat{\gamma}$	-0.34	-0.33	-0.39	-0.19
	$[-0.41,-0.25]$	$[-0.46,-0.20]$	$[-0.48,-0.29]$	$[-0.35,-0.01]$
$\hat{\lambda}$	9.19	9.44	9.95	8.22
	[8.27,10.28]	[8.01,11.13]	[8.43,11.39]	[6.95,9.69]
$LL(\hat{\gamma},\hat{\lambda})$	-2158	-757	-598	-795
# Obs.	2,700	900	900	900
# Ind.	150	150	150	150

Individual-cluster-robust bootstrapped 95% confidence intervals in brackets. The attribute-weighting function is defined by $g(\Delta_x;\gamma) = (\Delta_x)^\gamma$ for attribute $x \in \{q,p\}$. λ is the scale parameter of the type-1 extreme value error. Quality is defined as the average of the first- and second-stage reservation values.

regions. Table 6 columns (2) to (4) present the estimates. The qualitative results are similar for each of the experimental price regions, but the magnitude of range weighting is smaller in the o-decoy region. A likelihood-ratio test rejects the null of constant γ and λ across the three regions ($p < 0.01$). One possibility is that because prices are more visually salient than quality, range weighting is stronger when price is the dominant attribute range. However, while there is some variation in the magnitude of $\hat{\gamma}$ across the types of choice sets, it is negative and statistically significant in all three cases. Relative thinking is therefore supported across all three experimental decoy regions and offers a coherent explanation for the demand patterns documented in Section 3.

4.1 Economic Implications

The structural estimate of γ reported in the previous section is the first in the literature. In this section, I consider the economic implications of this estimate. Specifically, I quantify the willingness-to-pay premium for each of the three experimental decoy environments.

Suppose an individual has the quality perceptions implied by the average reservation values for the high- and low-quality variants: \$41 and \$24, respectively. Column (1) of Table 7 reports willingness-to-pay for the nondecoy options assuming surplus maximization, $\gamma = 0$. Column (3) reports willingness-to-pay conditional on the average realized price ranges for

$\hat{\gamma} = -0.34$. Columns (2) and (4) report willingness-to-pay at the upper and lower bounds of the 95% confidence interval for this estimate: -0.25 and -0.41, respectively.

Table 7: Quantifying Range-Dependent Attribute Weighting

	(1)	(2)	(3)	(4)
	Surplus Max	Lower Bound	Estimate	Upper Bound
Range weighting: $\gamma =$	0	-0.41	-0.34	-0.25
		Quality: $(q_h, q_l) =$ (\$41,\$24)		
***h*-decoy region** (p_h=\$62)				
Willingness-to-pay for l	\$24.0	\$28.4	\$27.6	\$26.6
% premium vs. surplus max	–	18.5%	15.1%	10.9%
***l*-decoy region** (p_l=\$66)				
Willingness-to-pay for h	\$41.0	\$49.8	\$48.2	\$46.2
% premium vs. surplus max	–	21.6%	17.6%	12.6%
***o*-decoy region** (p_h=\$28)				
Willingness-to-pay for l	\$11.0	\$15.0	\$13.1	\$12.5
% premium vs. surplus max	–	22.4%	18.8%	14.1%

Quality is set to the average reservation values reported in the experiment—\$41 and \$24 for the h and l variety. The price in each region is set to the average realized prices in each decoy region, and each region is defined using the average reservation values. The reported premiums are measured in percentage terms relative to the surplus maximization amount in column (1). The γ values are taken from column (1) of Table 6. Willingness-to-pay is (i) $WTP(\gamma) = q_l(q_h/p_h)^\gamma$ in the h-decoy region, (ii) $WTP(\gamma) = q_h(q_h/p_l)^\gamma$ in the l-decoy region, and (iii) defined implicitly by $(q_h/p_h)^\gamma = (p_h - WTP(\gamma))/(q_h - q_l)$ in the o-decoy region.

In the h-decoy region, the price of h sets the price range and exceeds the quality range. A negative γ coefficient implies that agents underweight price relative to quality, boosting willingness-to-pay for l relative to surplus maximization. For choice sets in this region, the average realized p_h was around \$62. This implies that an agent with $\hat{\gamma} = -0.34$ will be indifferent between buying l and not buying at a price of approximately \$27.6—a premium of around 15% relative to surplus maximization.

For prices in the l-decoy region, the price of l sets the price range and ensures that the price range exceeds the quality range. At the average realized p_l of \$66 in the data, an agent with $\hat{\gamma} = -0.34$ is willing to pay up to approximately \$48.2 to buy h—a premium of around 18% relative to surplus maximization.

In the o-decoy region, the low prices of both h and l mean that the quality range is greater than the price range. A surplus maximizer is willing to pay up to $p_h - (q_h - q_l) =$

\$28 − (\$41 − \$24) = \$11 to purchase l over h. A negative γ will cause agents to underweight prices and boost willingness-to-pay for l relative to h. Given an average realized p_h of \$28, an agent with $\hat{\gamma} = -0.34$ will be indifferent between h and l at p_l = \$13.1—a premium of around 19% relative to the surplus difference between h and l.

On average, participants were willing to pay an average premium of around 17% due to range weighting across the three decoy regions. In Table C.7 of Appendix C.4, I calculate the willingness-to-pay premium using alternative definitions of quality. Using the first-stage reservation values leads to a slightly lower average premium of 16%, while using the second-stage reservation values leads to substantially larger average premium of 26%.

5 Robustness and Alternative Theories

This section addresses three concerns. First, quality is uncertain and may be subject to bias or measurement error. A particular concern is that participants may have interpreted prices as signals of quality, which could generate demand shifts consistent with the data. Second, factors other than the immediate choice set may have influenced attribute weights; such as previous choice sets, expectations, or other reference points. Third, I explore whether the salience theory of Bordalo, Gennaioli, and Shleifer (2013) or pairwise normalization model Landry and Webb (2021) can provide an alternative explanation for the estimated choice probabilities.

5.1 Price as a Signal of Quality

Economists have explored the possibility that prices can signal quality. For example, Wolinsky (1983) shows that quality uncertainty can lead to an equilibrium in which prices credibly signal quality. In my experimental context, it is possible that higher prices boosted demand by signaling higher quality. This alternative form of choice-set dependence can generate predictions that are qualitatively similar to relative thinking under certain conditions.

Three conditions must hold for price signaling to explain my results. First, the perceived quality of option $j \in \{h, l\}$ must be increasing in the price of $k \neq j$. This leads to the prediction that higher decoy prices will boost buying in the h- and l-decoy price regions. Second, participants must judge the signal value of prices relative to their initial quality perceptions: for example, prices below their initial quality perceptions will lower their quality perceptions. This leads to a downward shift in the indifference boundary in the o-decoy price region. Finally, prices must provide a stronger signal of quality for h than for l. This ensures that parallel price increases in the o-decoy region can cause individuals to shift from l to h.

The data allow for direct tests of these three conditions. The experiment elicited two measures of participants' quality perceptions for both varieties of each good: one before seeing any prices and one after seeing two pairs of prices for each good. Participants were randomly assigned to h-, l-, or o-decoy prices on both encounters with a good, leading to nine possible price experiences. This creates exogenous variation in the price signals that participants saw for each good. To test whether these price signals affected quality perceptions, let $s_{ig} = (\bar{p}_{ig} - \bar{q}_{ig})$ be the signal value for good g for individual i, where $\bar{q}_{ig}$ is the average of the initial h- and l-quality perceptions and $\bar{p}_{ig}$ is the average of the h- and l prices in the experiment.[15]

To test whether observing higher price signals increased stated valuations, I regress the change in reservation value for individual i and good g on the signal index s_{ig}. The estimated coefficient implies that observing higher prices did lead to higher second-stage reservation values: a \$1 increase in the average prices increased quality perceptions by \$0.20 on average ($p < 0.001$). To test whether price signaling was equal for the h- and l varieties, I then interact the signal index s_{ig} with an indicator for the l variety. The estimated coefficient is small and not statistically different from zero—thereby rejecting a necessary condition for the price signaling model to provide a coherent explanation for my experimental results.

Even if price signals altered participants' quality perceptions, the key question is whether evidence of relative thinking is robust to controlling for these price signals. To separately identify the impact of relative thinking from price signaling, I exploit the panel structure of the data: specifically, that participants made two decisions involving each good. Consider a participant who first observes prices for some good g in the o-decoy region and receives a price signal of $-\$15$. Now suppose that on the next encounter with this product, the participant observes a price signal of $+\$15$, and therefore $s_{ig} = 0$. In this example, price

[15] Compared to alternative definitions of s_{ig} that directly involve q_j or p_k for $k \neq j \in \{h, l\}$, using average prices and qualities leads to predictions that most closely align with both relative thinking and the comparative-statics evidence. In Appendix C.2, I pursue alternative tests that do not rely on any functional form assumptions about the signal index and find similar results.

signaling would predict no demand shifts while relative thinking continues to predict the demand shifts outlined in Section 1.4. Table 8 builds on this intuition by analyzing data from participants' second encounter with each good. I repeat the analysis from Section 3 but restrict the data to the second set of decisions and control for the price signal index s_{ig}. If relative thinking is a robust phenomenon, then the prices of the decoy options should continue to provide explanatory power above and beyond their signal value.

Columns (1) to (3) of Table 8 confirm that the choice-probability estimates documented in Section 3 are robust to controlling for price signals. The estimated coefficients are similar in both direction and magnitude to the estimates in Table 4. In contrast, the price signal index s_{ig} has no significant effect on choice probabilities in any of the nine specifications.

The results in Table 8 rely on a specific parametric form of price-signaling index, s_{ig}. While this index does predict changes in valuations between the first and second stages of the experiment, it is possible that it is misspecified and only provides a noisy measure of the signal value contained in prices. In Appendix C.2, I implement an alternative approach in which I only consider the choices of participants who had previously saw a negative price signal on their first encounter with a given product. This approach makes no assumptions about the specific form of price signaling but does assume that participants at least partially remember previous price signals.[16] The results are qualitatively similar to those in Table 8 and show that relative thinking is robust even in situations in which price signaling predicts null or opposite effects.

In Appendix C.2, I also incorporate price signaling into my structural estimation. Specially, I estimate the equations:

$$q'_{ijt} = q_{ijt} + \alpha_j(\bar{p}_{it} - \bar{q}_{it}) \tag{2}$$

$$\mathcal{V}_{ijt} = 2\frac{(\Delta_{q'})^{\gamma}}{(\Delta_{q'})^{\gamma} + (\Delta_p)^{\gamma}}\, q'_{ijt} - 2\frac{(\Delta_p)^{\gamma}}{(\Delta_{q'})^{\gamma} + (\Delta_p)^{\gamma}}\, p_{ijt} + \lambda\varepsilon_j \tag{3}$$

where $\bar{p}_{it} = (p_{iht} + p_{ilt})/2$, $\bar{q}_{it} = (q_{iht} + q_{ilt})/2$ and $\alpha_o = 0$. The parameters α_h and α_l measure

[16] If participants forget previous price signals, then seeing a product earlier in the choice task or later in the second valuation task should weaken the impact of the price signals. To test this, I calculate the number of trials between each participant's second encounter with the product in the choice task and their next encounter the same product during second valuation task. I then estimate whether the change in valuations due to price signaling is moderated by this distance variable by interacting it with the signal index. I find no evidence that the impact of price signaling is moderated by the time between product encounters.

Table 8: Choice Probability Estimates – Second Half of Trials

	(1)	(2)	(3)
Dependent Variable:	Buy *high*	Buy *low*	Don't Buy
		Panel (a): *h*-decoy region	
Price of h	-0.20	0.48	-0.30
	(0.08)	(0.12)	(0.13)
s_{ig}	-0.04	0.25	-0.23
	(0.15)	(0.21)	(0.24)
		Panel (b): *l*-decoy region	
Price of l	0.62	0.02	-0.68
	(0.13)	(0.04)	(0.13)
s_{ig}	-0.01	-0.01	0.01
	(0.23)	(0.08)	(0.22)
		Panel (c): *o*-decoy region	
Price of h	0.88	-1.18	0.23
	(0.26)	(0.31)	(0.14)
s_{ig}	-0.27	0.39	-0.09
	(0.22)	(0.22)	(0.16)

Sample: Second half of experimental trials. Average marginal effects derived from logistic regression estimates. The specification includes participant demographics (age, gender, education, marital status and ethnicity) and round fixed effects. Demographic and round fixed are excluded from specification (2) for the l-decoy regressions due to the lack of variation in the outcome variable. The regressions either control for the price of l (panel a), the price of h (panel b), or the price difference between h and l (panel c). All numbers reported in percentages. s_{ig} measures the difference between the average prices individual i saw during the experiment for good g and their average first-stage reservation values for good g. There are 450 observations per region across 150 participants. Individual cluster-robust standard errors in parentheses.

the impact of price signaling on the h and l variants. I find that (i) the structural estimates are robust to incorporating price signaling and (ii) relative thinking provides the best fit to the data. Overall, while there is some evidence that higher prices led to an increase in quality perceptions, the patterns of demand documented in Section 3 are not driven by price signals. These results are consistent with Heffetz and Shayo (2009) who show that stated reservation values are sensitive to price signals, but estimated demand is not. Crucially, evidence supporting relative thinking is robust to controlling for price signals.

5.2 Features Beyond the Immediate Choice Set

In the main estimation in Section 4, I assume that agents evaluate each decision in isolation. However, external factors may have influenced participants due to the within-subjects design. Tversky and Simonson (1993) explicitly model these external factors as the "background context"; BGS distinguish the choice set from the "evoked set".

A particular concern in my experiment is that features of previous choice sets may impact subsequent decisions. While the product on offer (and hence the quality dimension) varied from trial to trial, price was a constant attribute across decisions, creating the potential for spillovers. For example, if an individual faces a relatively wide price range followed by a narrow one, they might not fully acclimate to the new price range. In Appendix C.3, I develop and estimate an alternative structural model that incorporates lagged prices into the evaluation of the current price range. The results show that previous price ranges have a statistically significant but small impact on attribute weights. More importantly, γ estimates are robust to controlling for this lagged price dependency.

Observing two trials per product may have induced spillovers from one trial to another—for example, by creating an expectation regarding future prices. Recall that each of the first nine trials featured a unique product. To control for any sequential effects due to repeatedly observing a single product, I restrict the sample to the first nine observations per individual. Columns (2) and (3) of Table 9 show that estimated range weighting is more pronounced in the first half of trials, $\hat{\gamma} = -0.44$, than for the second half of trials, $\hat{\gamma} = -0.24$. One possibility is that repeated exposure to products may have weakened the influence of the immediate choice set—for example, participants may have internalized the experiment's global price range of $[\$0.5, \$100]$ over time. This is consistent with the finding that previous price ranges had a small but statistically significant impact on the attribute weights. However, while the magnitude of the estimated coefficient is sensitive to whether the sample contains the first or the second half of trials, both estimates imply statistically significant range-dependent attribute weighting consistent with relative thinking.

Alternatively, repeated choices of any kind may have influenced participants. To completely remove any concerns owing to the within-subjects design, column (4) estimates the preferred specification using only the first choice from each individual. This pseudo between-

Table 9: Restricted Sample Estimates

	(1)	(2)	(3)	(4)
Sample:	Full	First Half	Second Half	First Choice Only
$\widehat{\gamma}$	-0.34	-0.44	-0.24	-0.30
	$[-0.42,-0.26]$	$[-0.53,-0.35]$	$[-0.34,-0.13]$	$[-0.49,-0.08]$
$\widehat{\lambda}$	9.19	9.13	9.13	8.03
	[8.18,10.27]	[8.13,10.29]	[7.79,10.71]	[5.80,11.09]
Individuals	150	150	150	150
Observations	2,700	1,350	1,350	150

Individual-cluster-robust bootstrapped 95% confidence intervals in brackets. The attribute weighting function is $(\Delta_x)^\gamma$ for attribute $x \in \{q, p\}$. λ is the scale parameter of the type-1 extreme value error. First half refers to trials 1 to 9. Second half refers to trials 10 to 18.

subjects design eliminates any confounds related to exposing participants to repeated choice sets at the expense of statistical power. Column (4) of Table 9 presents the results. The point estimate of -0.30 is close to the full sample estimate.

5.3 Alternative Theories of Choice-Set Dependence

5.3.1 Salience Theory

Bordalo, Gennaioli, and Shleifer (2012, 2013) (henceforth BGS) propose a closely related approach to choice-set dependence that differs from range theories in two important regards. First, they assume that attribute weights are specific to each option: for each alternative j agents compare quality and price to their average values in the choice set. Second, they posit that an attribute's extremity, rather than its range, determines its decision weight. They label this property "ordering": the more an attribute's value deviates from its average in the choice set, the greater its decision weight.

The ordering property of salience theory generates predictions that often line up with focusing: expanding an attribute's range in the choice set is often equivalent to increasing its difference with the mean. However, salience theory imposes a second, counteracting force: deviations from the mean are subject to diminishing sensitivity. This second motive induces a preference for high quality-to-price ratios, similar to relative thinking. For a subset of prices in the h-decoy region, the ordering effect will unambiguously dominate, and thus the predictions of salience theory will align with focusing.[17] To test whether the predictions of focusing and salience theory hold for this subset of prices, I re-estimate the choice probability models in Table 4 using only these trials. The estimated coefficients are again consistent with the predictions of relative thinking. For choice sets in which salience theory and relative thinking make distinguishing predictions, the data support relative thinking and are inconsistent with salience theory.

5.3.2 Pairwise Normalization

Landry and Webb (2021) propose a model of choice-set dependence in which individuals evaluate an option through a series of pairwise attribute comparisons. The value attached to each attribute comparison is normalized by the magnitude of the attributes under consideration. Both relative thinking and pairwise normalization are motivated by a central insight from perceptual neuroscience: neurons have a bounded response range and thus some form of normalization is necessary. In my experimental context, this shared intuition translates to shared predictions. Specifically, pairwise normalization reduces to a model in which attribute $x \in \{q, p\}$ is weighted by $1/(x_h + x_l)$. This formulation leads to the same predictions as the limiting case of relative thinking: agents choose h when $p_h/p_l < q_h/q_l$, l when $p_h/p_l > q_h/q_l$, and are indifferent between all three options when $p_h/p_l = q_h/q_l$. Therefore, pairwise normalization predicts that agents will always choose l in the h-decoy region, h in the l-decoy region, and l in the o-decoy region. This prediction is clearly inconsistent with the high proportion of not buying decisions made by participants in the h- and l-decoy regions and the high fraction of h choices in the o-decoy region (see Table 2).

Landry and Webb (2021) propose a generalization of their model in which a single parameter, $\sigma \geqslant 0$, indexes the strength of attribute normalization. The model reduces to the basic specification above when $\sigma = 0$ and converges to surplus maximization as $\sigma \to \infty$. For $0 < \sigma < \infty$, the predictions of the model are qualitatively similar to relative thinking in each of the three decoy regions. Increasing the price of the decoy option decreases price sensitivity in the h- and l-decoy regions, boosting demand for l and h, respectively. In the o-decoy region, increasing the price level while holding price differences fixed causes demand

[17] Formally, if the salience-theory weighting function satisfies ordering and homogeneity of degree zero, then price is always salient for both h and l for the set of prices $G \equiv \{(p_h, p_l) \in \mathbb{R}^2_+ : p_h \geqslant q_h \text{ and } q_l/p_l \geqslant q_h/p_h \text{ and, } q_l \leqslant q_h/2 \text{ or } p_h \geqslant p_l(8q_l - q_h)/(q_h + q_l)\}$.

to shift toward h. Therefore, the nonparametric evidence presented in Section 3 is consistent with both relative thinking and the one-parameter generalization of pairwise normalization.

6 Discussion

This paper provides a nonparametric test of relative thinking versus focusing and the first structural estimates of range-dependent attribute weighting. In a lab experiment, I find that expanding the price range causes participants to become less price sensitive and more likely to buy. I find little heterogeneity in attribute weighting across individuals; the majority of participants' behavior was consistent with relative thinking and few made choices consistent with focusing. The data are also inconsistent with utility maximization and existing formulations of salience theory.

The consistency of the results is particularly noteworthy: the predictions of relative thinking hold across individuals, trials, products, and price regions. Of course, the generalizability of any laboratory findings requires further research to establish the broader relevance of range weighting in real-world economic situations. However, the consistency of the results, and the psychological underpinnings of the theoretical predictions, bolster confidence in the mechanism underlying range-based attribute weighting.

Models of choice-set dependence are still developing and this paper only considers a subset of prominent theories. Similar models include Cunningham (2013) and Arad and Maltz (2019); related approaches include limited attention models (Dahremöller and Fels, 2015, Gabaix, 2014), computational models (Tsetsos, Usher, and Chater, 2010), informational asymmetries (Kamenica, 2008), and models of bargain utility (Jahedi, 2016). The approaches I focus on in this paper were chosen primarily for their structural similarity and their amenability to experimental testing. However, my primary empirical results show that models of choice-set-dependent preferences are well-founded and empirically relevant, and also offer potential guidance on refinements to these models.

While the data do not support existing formulations of salience theory, Bordalo, Gennaioli, and Shleifer (2020) have recently proposed an alternative version of their model that might be more consistent with the experimental data. Bordalo, Gennaioli, and Shleifer (2020) assume that deviations from memory-based norms, rather than the average in the choice set, generate departures from surplus-maximizing behavior. While my experiment was not designed to test for memory effects, some of the results are qualitatively consistent with norm-based expectations. For example, the low prices of both the low- and the high-quality options in the o-decoy region may come as a surprise relative to the participant's memory of the first stage. This price shock can cause agents to overweight prices in the Bordalo, Gennaioli, and Shleifer (2020) model and is therefore consistent with the experimental data from this region. However, the high prices of the high-quality good in the h-decoy region and the low-quality good in the l-decoy region should also induce heightened price sensitivity. Thus, the qualitative predictions of memory-based salience are inconsistent with data from the h- and l-decoy regions. While my data are not consistent with specific form of memory effects posited by Bordalo et al. (2020), understanding how memory interacts with choice-set dependence is a promising avenue for future work.

Despite robust evidence of relative thinking documented in this paper, there are many unresolved issues that limit the application of range weighting models. First, the cognitive mechanisms underlying range weighting are poorly understood. Relative thinking is motivated by perceptual encoding constraints, while the intuition of focusing emphasizes the importance of limited attention. How these forces interact with the complexity of the choice set is an open question. This has important economic implications in light of conflicting evidence on range weighting; while I document consistent evidence for relative thinking in a simple choice environment, other work has supported the predictions of focusing in more complex settings, such as intertemporal choice (Dertwinkel-Kalt et al., 2021). Whether a trip to the grocery store, buying car insurance, or online shopping are simple or complex decisions is unclear. A deeper understanding of what factors drive range weighting can help define the boundaries of relative thinking and focusing, and provide empirical guidance on how and when to apply these models.

Second, a major degree of freedom in most models of choice-set dependence is specifying the set of factors that influence the attribute weights. My experiment was designed to maximize the likelihood that participants considered each decision in isolation. However, I also present evidence that external factors entered into subjects' considerations. For example, previous prices had a statistically significant but small impact on how attributes were weighted. Furthermore, attribute weighting was less pronounced in the second half of the experiment, which may suggest that the local range set by the choice set was offset by a more global reference point. A more thorough understanding of which features of the choice environment influence attribute importance is needed, especially in real-world applications.

My results also highlight a form of choice-set dependence that has received less attention in the literature. I find evidence that prices may shape quality perceptions: participants who see higher prices during the choice task report higher second-stage valuations but the demand estimates are robust to controlling for these signals. These results are consistent with Heffetz and Shayo (2009) but are not easily accommodated by existing models of choice-set dependence. While I show that evidence of relative thinking is robust to price signaling, I cannot fully rule out this potential confound without making some assumptions about the learning process. To disentangle the effects of relative thinking and price signaling, future work could focus on situations in which the two models make opposite predictions. For example, a higher wage rate might signal that a task is more profitable, yet relative thinking would predict decreased sensitivity to wages. Alternatively, researchers could remove price signaling concerns entirely and control for visual salience by examining non-monetary situations, such as receiving products in exchange for effort provision.

Finally, further empirical guidance is required on which features of the choice set matter for attribute weighting. While I have shown that range is a useful proxy for choice-set dependence in simple choice environments, I cannot rule out similar determinants such as variance, maximum sensitivity, or divisive normalization. A systematic understanding of how price elasticities respond to exogenous changes in the features of the choice set would provide much-needed clarity on the fundamentals of choice-set dependence.

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