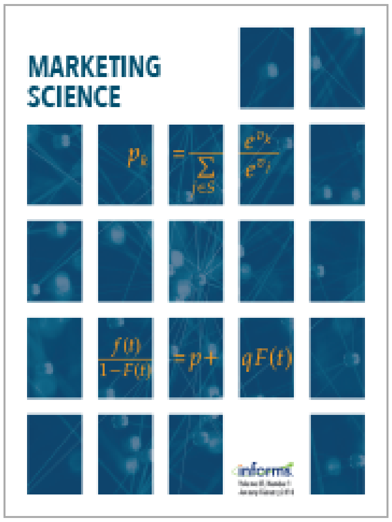

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Noncompensatory Dyadic Choices

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Whereas literature in marketing shows that individuals often use noncompensatory decision rules, existing research on dyadic choice is based on compensatory models. In this paper we present a dyadic consider-then-choose model that investigates both compensatory and noncompensatory aspects of the joint decision process. The intersection of individual consideration sets at the dyad level gives rise to dyadic decision processes (DDPs) where dyad members are in concordance or discordance about alternatives to consider. We empirically investigate the implications of different DDPs on outcomes such as decision efficiency and dyadic welfare. The methodological approach merges choice experiments with Bayesian statistical models to uncover nuances of the dyadic choice process. Data were collected using a multiphase nationwide study of 265 husband-and-wife dyads. Results across three categories indicate that both concordant and discordant dyads exist. Among concordant dyads, the noncompensatory dyads make quicker decisions that result in higher dyadic welfare. Among discordant dyads, those that restrict their consideration set make quicker decisions that result in higher welfare than those that expand their consideration set. These findings have important implications for buyers looking to maximize dyadic welfare when making joint choices and for sellers making pricing and new product design decisions.

Key words: group decision making; group welfare; joint choice; choice heuristics; hierarchical Bayes; consideration sets
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1. Introduction

Existing research on the topic of how a group makes choices (Davis 1970, Corfman and Lehmann 1987, Menasco and Curry 1989, Arora and Allenby 1999, Aribarg et al. 2010) assumes that the underlying utility function of a group is compensatory. That is, a group includes all available choice alternatives for consideration and trades off all product features against each other. This assumption is at odds with empirical evidence supporting the presence of consideration sets that suggests a noncompensatory choice process. Whereas attribute-based consideration at the individual level is well documented (Elrod et al. 2004, Jedidi and Kohli 2005, Gilbride and Allenby 2006, Yee et al. 2007), how this noncompensatory process unfolds in a joint choice context is not. The knowledge gap in how groups within an organization, or a family, make joint choices using noncompensatory decision rules is an important area of enquiry because it has direct implications for buyers and sellers.

The basic premise of this paper is that individual and dyadic consideration sets are inextricably related, and a careful investigation of this interrelationship, although important, has been largely neglected. Our goals in this paper are twofold. First, we develop a novel conceptual framework to empirically investigate the dyadic noncompensatory choice processes, and we evaluate both the quality and efficiency of those dyadic decisions. Second, we link dyadic noncompensatory choice processes to substantive marketing problems such as product design and pricing. We argue that a careful understanding of noncompensatory dyadic choices is of great interest to buyers and sellers alike. For buyers it provides prescriptions that maximize dyadic welfare when making joint choices and do so efficiently. For sellers, it provides actionable pricing and new product design insights that a compensatory model likely misses.

The dyadic choice process we propose builds on the two-stage "consider-then-choose" class of models

(Bettman 1979, Gilbride and Allenby 2004, Jedidi and Kohli 2005) and utility aggregation theories (e.g., Harsanyi 1955, Curry et al. 1991, Arora and Allenby 1999). Our primary focus is on the consideration stage of the model, where an individual or a dyad can eliminate product alternatives from consideration because they contain undesirable attribute levels such as a high price. Based on parameters that capture such screening, we introduce a set of mutually exclusive, collectively exhaustive dyadic decision processes (DDPs) that capture alternative ways in which consideration set differences between dyad members are reconciled.

In our DDP framework, the intersection of member-level consideration sets leads to dyads that are either concordant or discordant. We describe dyadic concordance as the case when dyad members agree on which alternatives to consider. Within this concordant group, we study differences between dyads that engage in a compensatory decision process for all available alternatives versus dyads that agree to only consider a smaller subset of alternatives. When dyad members disagree on which alternatives to exclude from consideration, there is dyadic discordance. For the discordant group, we examine the differences between dyads that choose to *expand* their consideration set, thus electing to evaluate a larger choice set, versus those that choose to *restrict* it and evaluate a smaller choice set. We draw contrasts between the alternative decision processes that result when dyads reconcile their consideration set differences using a variety of measures that assess decision efficiency (e.g., how quickly a dyad decides) and decision quality (e.g., dyadic welfare).

Our methodological approach merges choice experiments with statistical modeling to uncover the nuances of the noncompensatory dyadic choice process. The underlying econometric model uses Bayesian methods to account for member and dyad heterogeneity in consideration sets and preferences. Data for the research were collected with the help of C&R Research and involved a carefully constructed multiphase nationwide study of 265 husband-and-wife dyads. We report results pertaining to three consumer electronics products (flat-panel televisions, digital cameras, and laptop computers) and test our dyadic consider-then-choose model. In-sample and out-of-sample fit statistics demonstrate that our model outperforms a dyadic compensatory model. We also show that stated data provide useful information about the consideration stage of the model and significantly add to the model fit.

Beyond superior model fit, a bigger difference between the dyadic noncompensatory and compensatory models is that the former allows us to uncover the DDP framework and its unique insights—the primary focus of this paper. In particular, comparisons between dyads that follow alternate decision processes uncover significant differences in their decision efficiency and decision quality. Among dyads that are concordant, those that consider only a subset of alternatives make quicker and better choices than those that consider all available alternatives. Among discordant dyads, when compared to dyads that expand their consideration set, dyads that restrict their consideration set make quicker decisions that result in higher dyadic welfare. These findings align with behavioral economics literature related to information overload and overchoice (e.g., Iyengar and Lepper 2000, Schwartz 2004) but are at odds with the notion of equity, fairness, and reciprocity (Deutsch 1975, Albin 1993) likely present in intact dyads.

The dyadic noncompensatory model also offers a distinct substantive advantage over the extant compensatory model. For example, we show that in contrast to our model, a dyadic compensatory model not only understates demand in a demand forecast for a new product, it also suggests an optimal price that is significantly lower. The primary reason for these differences is that unaccounted-for price screening in a compensatory model can bias the price sensitivity estimates upward. A dyad's willingness to pay for a specific feature is also found to be closely tied to its consideration set that a compensatory model fails to detect. Therefore, compared with the proposed dyadic consider-then-choose model, a dyadic compensatory model can suggest a suboptimal price, incorrectly predict demand, and result in less profitable decisions.

The remainder of this paper is organized as follows. We begin with a section that outlines our conceptual framework and dyadic noncompensatory model. This is followed by a detailed description of our study and data collection procedure. Section 4 contains our findings from the multiphase study, and in §5 we present model extensions. We conclude the paper with a discussion of our findings.

2. Conceptual Framework and Model

Noncompensatory decision rules involve exclusion of certain attributes for consideration. Such screening rules are obtained directly via stated measures (Yee et al. 2007) or are model based (Gilbride and Allenby 2006). Our approach does both: using stated data as prior information when estimating model-based screening parameters. An intersection of individual screening parameters at the dyad level gives rise to our decision framework that we explain next.

2.1. Dyadic Consider-Then-Choose Model Specification

We describe our modeling framework for a situation in which two individuals (say, husband h and wife w) jointly make a decision to choose a product. Let us assume that the husband h evaluating K alternatives within a choice set chooses alternative k'. Each alternative k ($k = 1, \ldots, K$) has a design vector x_k indicating the presence ($x_{km} = 1$) or absence ($x_{km} = 0$) of attribute levels $m = 1, \ldots, M$. The deterministic part of utility V_{hk}, linear in the predictor variables ($x_k' \beta_h$), with an independent and identically distributed Type I extreme value error structure, yields a multinomial logit model of choice (McFadden 1974). To capture the noncompensatory evaluation process, a parameter (τ_{hm}) is included for each attribute level m, where $\tau_{hm} = 1$ if the attribute level is screened out and $\tau_{hm} = 0$ otherwise (Gilbride and Allenby 2006). An indicator function $\mathbf{I}(x_k, \tau_h)$ governs the inclusion of an alternative in the consideration set as follows:

$$\Pr_h(k') = \Pr\big(V_{hk'} + \varepsilon_{hk'} > V_{hk} + \varepsilon_{hk} \quad \forall k \text{ such that } \mathbf{I}(x_k, \tau_h) = 1\big),$$

$$\text{where} \quad \mathbf{I}(x_k, \tau_h) = \begin{cases} 0 & \text{if } \sum_{m=1}^{M} (\tau_{hm} \times x_{km}) \geq 1, \\ 1 & \text{otherwise.} \end{cases} \tag{1}$$

That is, alternative k is not considered if there exists an attribute level m in alternative k ($x_{km} = 1$) such that the attribute level is screened out ($\tau_{hm} = 1$). Stated differently, an alternative k is considered if all attribute levels in the alternative pass screening. The indicator function $\mathbf{I}(x_k, \tau_h)$ partitions the error space and results in the following expression for choice probability:

$$\Pr_h(y_{k'} = 1) = \frac{\mathbf{I}(x_{k'}, \tau_h) \exp(x_{k'}' \beta_h)}{\sum_{k=1}^{K} \mathbf{I}(x_k, \tau_h)[\exp(x_k' \beta_h)]}. \tag{2}$$

Analogous to $\{\beta_h, \tau_h\}$ for husband h, there exist parameters $\{\beta_w, \tau_w\}$ for wife w such that

$$\Pr_w(y_{k'} = 1) = \frac{\mathbf{I}(x_{k'}, \tau_w) \exp(x_{k'}' \beta_w)}{\sum_{k=1}^{K} \mathbf{I}(x_k, \tau_w)[\exp(x_k' \beta_w)]}. \tag{3}$$

Similarly, the dyadic choices made by the husband and wife together could be written as

$$\Pr_d(y_{k'} = 1) = \frac{\mathbf{I}(x_{k'}, \tau_d) \exp(x_{k'}' \beta_d)}{\sum_{k=1}^{K} \mathbf{I}(x_k, \tau_d)[\exp(x_k' \beta_d)]}, \tag{4}$$

where parameters $\{\beta_d, \tau_d\}$ capture attribute preference and screening for the dyad. The dyad's attribute preferences in the vector β_d are linked to the attribute influence vector ϕ_h of husband h in the dyadic choice decision (Arora and Allenby 1999) as

$$\beta_d = \phi_h \beta_h + (1 - \phi_h) \beta_w. \tag{5}$$

That is, dyadic preference is a linear function of individual member preferences. The parameter space of ϕ_h could be constrained to lie between 0 and 1 if dyadic preference is a convex combination of individual preferences. However, the group polarization phenomenon (Myers and Lamm 1976, Rao and Steckel 1991) suggests that dyadic preference may be more extreme than the average of individual prediscussion preference. Therefore, we refrain from imposing a range constraint ($0 \leq \phi_h \leq 1$) on the influence parameter. Compensatory dyadic influence of this type has been examined in prior research, but how the dyadic decision process unfolds in the noncompensatory context has not. Next, we describe our framework for characterizing the noncompensatory dyadic decision process, which is the primary focus of this paper.

2.2. Attribute-Level Noncompensatory Dyadic Decision Process

For a given attribute level, the intersection of the binary realizations of individual screening parameters $\{\tau_h, \tau_w\}$ creates a two-by-two matrix of possible noncompensatory dyadic decision states. These states can be classified into two categories: concordance and discordance. Concordance refers to states in which both h and w exhibit similar screening behavior ($\tau_h = \tau_w$): both parties are of the same mind to either consider or not consider the attribute level. Discordance, in contrast, refers to h and w having opposing screening behaviors ($\tau_h \neq \tau_w$): either h screens out the given attribute level and w does not ($\tau_h = 1, \tau_w = 0$), or vice versa ($\tau_h = 0, \tau_w = 1$). In the presence of the individual screening parameters just described, a dyad could subsequently screen ($\tau_d = 1$) or not screen ($\tau_d = 0$) on a given attribute level.

Connecting the dyad's screening behavior to member-specific screens creates four distinct characterizations of the noncompensatory dyadic decision process that are of particular interest to us. To illustrate this framework, we use a husband-and-wife automobile choice decision example. We begin by focusing on a single attribute level (the Toyota brand in our illustration) and subsequently expand the framework to account for the dyadic decision process across attributes. Although the term "dyadic decision process" (or "DDP") could refer to both the compensatory and noncompensatory dimensions of a joint decision, in this paper we restrict our use of the term DDP to encompass only the noncompensatory aspects of the model as expressed in the attribute-level screening parameters.

2.2.1. Compensatory Concordant ($\tau_h = \tau_w = 0$). For this DDP both h and w include alternatives with this attribute level in their consideration set. In our example, this implies that the husband and wife are of the same mind—as individuals, they are both willing to consider the Toyota brand in the trade-offs they make. At a later stage, as a dyad, they will mostly likely keep the Toyota brand in their consideration set ($\tau_d = 0$).

2.2.2. Screening Concordant ($\tau_h = \tau_w = 1$). Both h and w exclude alternatives with this attribute level. This suggests that Toyota, in our example, is an unacceptable alternative for both the husband and wife as individuals. At a later stage, as a dyad, they will mostly likely keep the Toyota brand out of their consideration set ($\tau_d = 1$).

2.2.3. Expand ($\tau_h \neq \tau_w, \tau_d = 0$). There is discordance about the attribute level: one member excludes alternatives with this attribute level while the other member does not. The dyad resolves the difference by *including* alternatives with this attribute level, thus expanding their consideration set. Expansion as a DDP is equivalent to a union (*or*) rule for consideration sets. In our example, although Toyota is an unacceptable alternative for one individual and is acceptable to the other, upon deliberation, the dyad decides to include Toyota for consideration.

2.2.4. Restrict ($\tau_h \neq \tau_w, \tau_d = 1$). There is also attribute discordance here: one member excludes alternatives with this attribute level, but the other member does not. The dyad resolves the difference by *excluding* alternatives with this attribute level, thus restricting their consideration set. Restriction is equivalent to an intersection (*and*) rule for consideration sets. In our example, although Toyota is an unacceptable alternative for one individual and acceptable to the other, upon deliberation, the dyad decides to exclude Toyota as an alternative for consideration.

2.3. Across-Attribute Dyadic Decision Process

Our conceptualization of the noncompensatory dyadic decision process has thus far focused on only one attribute level, but most choices involve multiple attributes. Next, we extend the concordance, discordance, expand, and restrict concepts to the multiattribute context. This results in a potential fifth DDP that we also describe. For simplicity, we continue to use the term "DDP" instead of "DDP across attributes" when referring to the dyadic decision process across attributes. Table 1 lists the five DDPs that emerge in a multiattribute setting. To exemplify each DDP type, we extend our husband-and-wife automobile choice decision illustration to include two attributes—brand and color—each with two levels. The brands in our example are Honda and Toyota, and the colors are black and white.

In a multiattribute setting, dyads that exhibit compensatory concordance across all levels of *all* attributes are classified as compensatory concordant DDP. That is, for such dyads, $\tau_{hm} = \tau_{wm} = 0$ for all attribute levels $m = 1, \ldots, M$. In this paper, the compensatory concordant DDP is referred to in abbreviated notation as CC. In our automobile example in Table 1, this is the first DDP. Notice that both the husband and wife are in agreement and do not engage in screening—they consider both brands and both colors. As a dyad, they follow the "all-in" strategy and trade off between brands and colors when making a choice. Moving to the next DDP, dyads that are concordant across all attributes and exhibit screening concordance for *at least one* attribute level are classified as screening concordant DDP. That is, $\tau_{hm} = \tau_{wm}$ for all attribute levels $m = 1, \ldots, M$, and for at least one m, $\tau_{hm} = \tau_{wm} = 1$. We refer to the screening concordant DDP as SC. In our example of an SC in Table 1, both the husband and wife are in agreement and exclude white cars. As a dyad, they only consider black cars and trade off between the two brands when making a choice.

Discordance in a multiattribute setting occurs when for at least one attribute level m, $\tau_{hm} \neq \tau_{wm}$. In such instances resolution of the differences can occur via expansion, restriction, or a combination of the two mechanisms. To be classified in the expand DDP, a dyad must decide to include for consideration *all* m^* attribute levels on which there is screening discordance between individual dyad members—that is, for set expansion $\tau_{dm} = 0$ for all m, where $\tau_{hm} \neq \tau_{wm}$. In the example of an expand DDP in Table 1, $m^* = 2$ because there is screening discordance on two attribute levels: the husband excludes the Toyota brand and white cars from consideration, but the wife is willing to consider all brands and colors. Dyads using the expand DDP do not exclude any alternatives and trade off all brands and colors when making a choice.

The restrict DDP describes dyads that decide to exclude from consideration *all* m^* attribute levels on which there is screening discordance between individual dyad members. This dyadic consideration set restriction is expressed as $\tau_{dm} = 1$ for all m, where $\tau_{hm} \neq \tau_{wm}$. For the example in the fourth block of Table 1, notice that the consideration set for a restrict DDP is smaller—the husband and wife only consider black and white Hondas. Finally, in cases where there is screening discordance across multiple attributes, a dyad may choose to pursue a mixed strategy—expanding its consideration set for some attributes and restricting it for other attributes. The husband in our example of a mixed DDP excludes Toyota, and the wife excludes the color white. The dyad restricts its consideration set on one aspect of the decision (only black color) and expands on the other (both Honda and Toyota brands).

2.4. Parameter Heterogeneity

Whereas our model development until this point has focused on a given dyad, preference, influence, and

Table 1 Across-Attribute DDP Illustration

DDP	Compensatory concordance $\sum_m \mathrm{I}\{\tau_{hm} \neq \tau_{wm}\} = 0 \wedge \sum_m \mathrm{I}\{\tau_{hm} = \tau_{wm} = 1\} = 0$		
Screening parameters	$\tau_{h1} = \tau_{h2} = \tau_{h3} = \tau_{h4} = 0$ Husband	$\tau_{w1} = \tau_{w2} = \tau_{w3} = \tau_{w4} = 0$ Wife	$\tau_{d1} = \tau_{d2} = \tau_{d3} = \tau_{d4} = 0$ Dyad
Consideration set	Honda ■ Toyota □	Honda ■ Toyota □	Honda ■ Toyota □
DDP	Screening concordance $\sum_m \mathrm{I}\{\tau_{hm} \neq \tau_{wm}\} = 0 \wedge \sum_m \mathrm{I}\{\tau_{hm} = \tau_{wm} = 1\} \geq 1$		
Screening parameters	$\tau_{h1} = \tau_{h2} = \tau_{h3} = 0$, $\tau_{h4} = 1$ Husband	$\tau_{w1} = \tau_{w2} = \tau_{w3} = 0$, $\tau_{w4} = 1$ Wife	$\tau_{d1} = \tau_{d2} = \tau_{d3} = 0$, $\tau_{d4} = 1$ Dyad
Consideration set	Honda Toyota ■	Honda Toyota ■	Honda Toyota ■
DDP	Expand $\sum_m \mathrm{I}\{\tau_{hm} \neq \tau_{wm}\} = m^* \geq 1 \wedge \sum_{m \in \{m: \tau_{hm} \neq \tau_{wm}\}} \mathrm{I}\{\tau_{dm} = 0\} = m^*$		
Screening parameters	$\tau_{h1} = \tau_{h3} = 0$, $\tau_{h2} = \tau_{h4} = 1$ Husband	$\tau_{w1} = \tau_{w2} = \tau_{w3} = \tau_{w4} = 0$ Wife	$\tau_{d1} = \tau_{d2} = \tau_{d3} = \tau_{d4} = 0$ Dyad
Consideration set	Honda ■	Honda ■ Toyota □	Honda ■ Toyota □
DDP	Restrict $\sum_m \mathrm{I}\{\tau_{hm} \neq \tau_{wm}\} = m^* \geq 1 \wedge \sum_{m \in \{m: \tau_{hm} \neq \tau_{wm}\}} \mathrm{I}\{\tau_{dm} = 1\} = m^*$		
Screening parameters	$\tau_{h1} = \tau_{h3} = \tau_{h4} = 0$, $\tau_{h2} = 1$ Husband	$\tau_{w1} = \tau_{w2} = \tau_{w3} = \tau_{w4} = 0$ Wife	$\tau_{d1} = \tau_{d3} = \tau_{d4} = 0$, $\tau_{d2} = 1$ Dyad
Consideration set	Honda ■ □	Honda ■ Toyota □	Honda ■ □
DDP	Mixed $\sum_m \mathrm{I}\{\tau_{hm} \neq \tau_{wm}\} = m^* \geq 1 \wedge \sum_{m \in \{m: \tau_{hm} \neq \tau_{wm}\}} \mathrm{I}\{\tau_{dm} = 0\} \geq 1 \wedge \sum_{m \in \{m: \tau_{hm} \neq \tau_{wm}\}} \mathrm{I}\{\tau_{dm} = 1\} \geq 1$		
Screening parameters	$\tau_{h1} = \tau_{h3} = \tau_{h4} = 0$, $\tau_{h2} = 1$ Husband	$\tau_{w1} = \tau_{w2} = \tau_{w3} = 0$, $\tau_{w4} = 1$ Wife	$\tau_{d1} = \tau_{d2} = \tau_{d3} = 0$, $\tau_{d4} = 1$ Dyad
Consideration set	Honda ■ □	Honda Toyota ■	Honda Toyota ■

screening parameters likely vary across the sample. Preference heterogeneity is captured by the following random-effects specification:

$$\theta_d \sim \mathrm{Normal}(\bar{\theta}, D). \tag{6}$$

In Equation (6), θ_d is a vector of individual (i.e., h and w) preference and influence parameters for the dth dyad. Specifically, $\theta_d = [\beta_{dh}, \beta_{dw}, \phi_d]$, and

$$\bar{\theta} = [\bar{\beta}_h, \bar{\beta}_w, \bar{\phi}] \quad \text{and} \quad D = \begin{bmatrix} D_{hh} & D_{hw} & D_{hd} \\ D_{wh} & D_{ww} & D_{wd} \\ D_{dh} & D_{dw} & D_{dd} \end{bmatrix}. \tag{7}$$

The hyperparameter vector $\bar{\theta}$ captures the central tendency of (husband-and-wife) preferences and influence. The diagonal elements of D demonstrate the extent of heterogeneity among husbands' preference (D_{hh}), wives' preference (D_{ww}), and influence (D_{dd}), whereas the off-diagonal elements capture preference and influence covariance.

For each attribute level, there are eight (i.e., 2^3) potential realizations of the husband, wife, and dyad binary screening parameters [τ_{dh}, τ_{dw}, τ_d]. We define ω_d to be the (8×1) vector that identifies a particular realization of the binary screening parameters [τ_{dh}, τ_{dw}, τ_d], and the heterogeneity of ω_d is captured through the following alternative model specifications.

2.4.1. Model 1. We assume that for a given attribute level m, the screening vector ω_{dm} follows a multinomial distribution with probabilities $p_{1m}, \ldots, p_{8m}$, where each probability indicates the proportion of the sample belonging to each one of the eight realizations of ω_{dm}. Thus,

$$\omega_{dm} \sim \text{Multinomial}(p_{1m}, \ldots, p_{8m}). \tag{8}$$

We specify a generalized Dirichlet distribution (Wong 1998) as the prior of the multinomial probabilities to allow for a more general covariance structure.[1] That is, $[p_{1m}, \ldots, p_{7m}] \sim$ generalized Dirichlet($\alpha_{1m}, \ldots, \alpha_{7m}, \zeta_{1m}, \ldots, \zeta_{7m}$), and $p_{8m} = 1 - p_{1m} - \cdots - p_{7m}$. As such, Model 1 is a multidimensional extension of the specification used in the conjunctive screening rule model of Gilbride and Allenby (2006).

In addition to bringing noncompensatory research to the joint decision-making domain, a novel aspect of our paper is that we leverage stated data to better understand the noncompensatory decision process. The next model provides a method in which stated measures of attribute screening obtained from respondents are used to improve parameter estimate efficiency.

2.4.2. Model 2. Stated measures of individual and dyadic propensity to screen certain attribute levels are easy to elicit. For example, previous research (Yee et al. 2007, Aribarg et al. 2010) uses "must have" or "can't have" classification schemes to assess screened-out attributes. Similarly, self-explicated approaches (Srinivasan and Park 1997) routinely rely on measures such as "most you will pay" or "lowest acceptable speed" to assess screening. In the presence of choice data, such stated data could be of significant value (Horsky et al. 2006) because they help inform the screening probabilities in Equation (8). This is particularly important in our context because the model includes individual-level parameters, so the total number of parameters is high.

It is reasonable to assume that the dyads' stated screening for each attribute level is indicative of actual screening behavior in the choices they make. For example, if a dyad states that it would consider all attribute levels across all attributes both as individuals and as a dyad, then it is reasonable to assume that it is quite likely that the dyad would do so during the choice task. Using the stated screening information that is often easy to collect, in Model 2 we translate stated data on screening into subjective probabilities. The multinomial ω_{dm} bin membership probability is specific to each dyad based on the information from the dyad's stated screening, so

$$\omega_{dm} \sim \text{Multinomial}(p_{d1m}, \ldots, p_{d8m}). \tag{9}$$

We incorporate dyad-specific stated screening information through a generalized Dirichlet prior as follows. Let $\omega^*_{dm} = \mathrm{w}^b$ denote that the stated screening for dyad d falls in the bth bin of the eight possible realizations. Because the order of elements in a generalized Dirichlet distribution is not arbitrary, we first rearrange the multinomial probabilities based on the self-stated screening bin membership by mapping $[p_{d1m}, \ldots, p_{d8m}]$ to $[p^*_{d1m}, \ldots, p^*_{d8m}]$ so that $p^*_{d1m} = p_{dbm}$ and $p^*_{dbm} = p_{d1m}$ if $\omega^*_{dm} = w^b$. Then,

$$[p^*_{d1m}, \ldots, p^*_{d7m}]$$
$$\sim \text{generalized Dirichlet}(\alpha^*_{1m}, \ldots, \alpha^*_{7m}, \zeta^*_{1m}, \ldots \zeta^*_{7m}), \tag{10}$$

where $\alpha^*_{bm}/(\alpha^*_{bm} + \zeta^*_{bm}) = \mu_b$ for $b = 1, 2, \ldots, 7$, and $p^*_{d8m} = 1 - p^*_{d1m} - \cdots - p^*_{d7m}$. The values of α^*_{bm} and ζ^*_{bm} can be determined according to prior beliefs about both $E(p^*_{dbm})$ and the expected standard deviation of p^*_{dbm}. The details of drawing $[p^*_{d1m}, \ldots, p^*_{d7m}]$ are provided in the appendix. Within this setup, dyads have a high expected probability of exhibiting the screening behavior they stated and a lower probability of falling into one of the other ω_{dm} bins.[2]

2.5. Consequences of Dyadic Decision Processes

Next, we study decision quality implications for both concordant and discordant dyads. In particular, (i) when concordant, do compensatory concordant dyads make better decisions than screening concordant dyads? And (ii) when discordant, which one of the three DDPs (expand, restrict, or mixed) results in better decisions for the dyad? Literature on consumer expertise and the use of choice heuristics (Alba and Hutchinson 1987) suggests that more knowledgeable dyads with well-formed preference structures will use screening to efficiently narrow the choice set and make high-quality decisions. Research also suggests that considering too many alternatives, as would be the case with compensatory dyads, leads to information overload, resulting in suboptimal outcomes (Keller and Staelin 1987, Gourville and Soman 2005, Kuksov and Villas-Boas 2010, Dhar 1997, Iyengar and Lepper 2000, Chernev 2003). Existing research therefore suggests that screening concordant dyads likely make better decisions than compensatory concordant dyads because these dyads focus on a smaller consideration set.

Unlike situations when preferences concord, previous research provides less conclusive guidance for situations when discord exists. From the standpoint of fairness and reciprocity, considering more alternatives, or an expand DDP, appears most equitable (Deutsch 1975, Albin 1993) and would likely have a

[1] This is in comparison to the standard Dirichlet distribution, which restricts the covariances of the multinomial probabilities to be negative. We thank the associate editor for raising this issue.

[2] An alternative approach to incorporate stated screening data would be to use them as a covariate for the hyperparameter vector in Equation (8). Fit statistics from this alternative model (available from the authors upon request) were inferior to the proposed Model 2 and are therefore excluded.

positive impact on decision quality. In contrast, the "overchoice" literature suggests that a restrict strategy might be better because it helps focus the dyads on a more manageable consideration set.

In the empirical section that follows, we examine the implications of different DDPs on decision quality using the following three specific measures: concession, choice inefficiency, and dyadic preference intensity, which can be thought of as proxies for dyadic welfare/happiness.

2.5.1. Concession. Concession for a given dyad measures the compromises that individual members of the dyad make during the joint choice decision process (Corfman and Lehmann 1993, Aribarg et al. 2002). Specifically, for a particular dyadic joint choice task, let ideal_h (ideal_w) represent the alternative with maximal utility that the husband (wife) would have chosen based on his (her) individual preferences, and let chosen_d represent the actual alternative chosen jointly by the dyad. We define dyadic concession as

$$\text{Concession}_d = [\Pr_h(\text{ideal}_h) - \Pr_h(\text{chosen}_d)] + [\Pr_w(\text{ideal}_w) - \Pr_w(\text{chosen}_d)]. \quad (11)$$

2.5.2. Choice Inefficiency. Although a dyad is expected to maximize utility and choose the ideal alternative, this may not always occur. Therefore, we define the choice inefficiency measure as the deviation of the dyad's chosen alternative from the dyad's ideal alternative as

$$\text{Choice inefficiency}_d = \Pr_d(\text{ideal}_d) - \Pr_d(\text{chosen}_d). \quad (12)$$

2.5.3. Dyadic Preference Intensity. The concepts of welfare (Gupta and Kohli 1990) and regret (Inman et al. 1997) suggest that dyads selecting an alternative with larger relative attractiveness are likely to be happier than those dyads that select an alternative with a smaller relative attractiveness. We define dyadic preference intensity as the relative attractiveness (choice probability) of the dyad's chosen alternative:

$$\text{Dyadic preference intensity}_d = \Pr_d(\text{chosen}_d). \quad (13)$$

Next, we describe a study we designed to (i) test the proposed dyadic noncompensatory choice model, (ii) empirically investigate the prevalence of alternative dyadic decision processes and their subsequent impact on decision efficiency and quality, and (iii) investigate the substantive implications of the dyadic noncompensatory model on managerial decisions involving product design and pricing. In our study design, we paid particular attention to how stated measures of individual and dyadic screening were obtained, because these measures lie at the heart of the dyadic decision processes we hope to uncover.

3. Empirical Study

The study was completed by 265 married couples in an online panel environment managed by C&R Research and had several stages that involved individual and joint tasks, as summarized in Table 2. Because of its multistage nature, in addition to the usual reward points for an opt-in panel, the respondents were given $15 for completing the survey and also had a chance to win a flat-panel television. The study involved three durable goods categories (laptop computers, digital cameras, and flat-panel televisions), and dyads qualified on the basis of likelihood to buy a flat-panel TV. Next, we explain each stage of the study in detail.

3.1. Individual Preference Measurement (Laptop Computer or Digital Camera)

A subset of the full sample indicated that it was likely to buy a laptop computer or a digital camera over the next 12 months. For one of these two categories, we asked the qualifying dyads specific questions pertaining to their product attribute preferences. Laptop computer attributes included brand name (e.g., Apple, Gateway), features (e.g., Intel processor, quad-core architecture), and price. Similarly, digital camera attributes included brand (e.g., Nikon, Sony), features (e.g., 10-megapixel resolution, 5× zoom), and price. The respondents were provided a brief overview of each attribute and then asked to drag and drop each attribute level into one of the three attribute classification bins: "can't have this feature," "it depends," or "must have this feature." Taken as a proxy for screening, the "can't-have" category indicates that alternatives with this attribute would not be found in the respondent's consideration set. In addition to the attribute classification task, we asked individuals category-specific questions about product usage, experience, and knowledge.

3.2. Individual Preference Measurement (Flat-Panel TV)

Similar to the aforementioned categories, measures of stated preference, experience, knowledge, etc., were also obtained for the flat-panel TV category. The specific attributes we used are listed in Table 3. In addition to these stated measures, respondents also completed a choice-based conjoint session with 14 choice tasks, each involving four alternatives, which were used to estimate his or her preferences. A blocked design involving four sets of 14 such quads using the attributes and levels in Table 3 was created using SAS OPTEX. When performing these choice tasks, members were instructed to make choice decisions based on their *own* preferences.

Following individual preference measurement, the first spouse then provided detailed data on measures such as personality traits and demographics.

Table 2 Study Flow

Stage	First spouse	Second spouse
1	**Screening questions** Purchase likelihood of TV, laptop, camera	
2	**Individual preference measurement** *Stated*: Must have; it depends; can't have (TV plus laptop or camera) [see §3.1] *Model based*: Choice-based conjoint task (TV only) [see §3.2] **Respondent characteristics** Individual attitudes, personality traits, context-specific measures, and demographics	
		Individual preference measurement *Stated*: Must have; it depends; can't have (TV plus laptop or camera) [see §3.1] *Model based*: Choice-based conjoint task (TV only) [see §3.2]
3	**Joint preference measurement** *Stated*: must have; it depends; can't have (TV only) [see §3.3] *Model based*: choice-based conjoint (TV only) [see §3.3] **Joint shopping task** (TV only) [see §3.4]	
4		Post-joint choice measures [see §3.5] **Respondent characteristics** Individual attitudes, personality traits, context-specific measures, and demographics
	Post-joint choice measures [see §3.5]	

Upon completion, we contacted the second spouse via e-mail and asked him or her to provide the exact same information—including the identical choice task—as the first spouse.

3.3. Joint Preference Measurement (Flat-Panel TV Only)

After the second spouse finished the individual preference measurement task, he or she was instructed to complete the next section of the study jointly with the first spouse. If the first spouse was unavailable, the second spouse was asked to save the survey link and click it when they were both ready. First, the dyad was asked to drag and drop a series of TV attribute levels into one of three categories: must have this feature, it depends, or can't have this feature. Next, dyads completed a choice-based conjoint session with 14 choice tasks, each involving four alternatives, which were used in estimating the dyad's preferences. The 14 choice tasks were different from the set the spouses had individually completed. When performing these tasks, dyads were instructed to make choice decisions jointly. Specifically, they were told,

> Please feel free to discuss your likes and dislikes with each other. There is no right or wrong answer. We are simply interested in knowing which flat-panel TV the two of you would select together.

Table 3 Flat-Panel Television Choice-Based Conjoint Study Attributes and Levels

Brand	Sony	Panasonic	Vizio	Samsung
Screen size	32"	42"	52"	
Warranty	Standard	Extended		
Picture technology	LCD	Plasma		
Resolution	720p	1080p		
Price ($)	699	999	1,299	1,599

3.4. Joint Shopping Task (Flat-Panel TV Only)

In this section the dyads were asked to visualize shopping together for a flat-panel TV at a number of different online retailers. Their task was to select one flat-panel TV that the dyad would be most interested in buying. They were given the option to click on links to one of six highly rated retailer websites (Abt, Onecall, J&R, TigerDirect, Crutchfield, or Vann's) and view an assortment of flat-panel televisions. Each retailer in our study carried six flat-panel TV models, so, in total, the dyads had 36 options from which to choose. Dyads could visit the retailers in our study as many times as they wanted. The dyadic part of the survey ended after a TV selection was made by the dyad. The first spouse was thanked at this stage,

Table 4 Laptop and Camera Stated Attribute Classification Proportions

	Husband-stated attribute classification			Wife-stated attribute classification		
Proportion of sample in each category by attribute	Can't have	It depends	Must have	Can't have	It depends	Must have
Laptop computer						
Apple	0.330	0.592	0.078	0.291	0.612	0.097
Gateway	0.291	0.709	0.000	0.233	0.738	0.029
Intel processor	0.039	0.515	0.447	0.010	0.515	0.476
Quad-core	0.019	0.650	0.330	0.000	0.748	0.252
Price $\leq$ \$799	0.000	0.583	0.417	0.000	0.592	0.408
Digital camera						
Nikon	0.083	0.854	0.063	0.052	0.854	0.094
Sony	0.042	0.885	0.073	0.031	0.885	0.083
At least 10 megapixels	0.021	0.521	0.458	0.021	0.479	0.500
At least 5$\times$ zoom	0.021	0.375	0.604	0.010	0.354	0.635
Price $\leq$ \$199	0.000	0.510	0.490	0.000	0.479	0.521

and the survey continued with the second spouse to obtain the final set of measures.

3.5. Post-Joint Choice Measures

The second spouse was asked about the extent of disagreement and the resolution process in the joint choice task. As a separate follow-up, the first spouse was asked the exact same questions.

4. Results

A total of 265 dyads finished the study. The respondents were mostly white (83%), represented all regions of the United States (Northeast = 22%, Midwest = 32%, South = 34%, and West = 12%), and came from a wide spectrum of household incomes (<\$35,000 = 14%, and >\$100,000 = 15%) and family sizes (≤1 child = 18%, and ≥4 children = 22%). By design, all 265 dyads provided data on the flat-panel television category—these dyads qualified for the study based on a purchase likelihood question. A subset of these dyads also provided data for either the laptop ($n = 103$, 39%) or the digital camera ($n = 96$, 36%) because these dyads indicated that they were likely to buy in that category as well. We begin by looking at results based on stated can't-have, it-depends, and must-have measures as outlined in §3.1.

4.1. Inference Based on Stated Measures (Laptop Computer and Digital Camera)

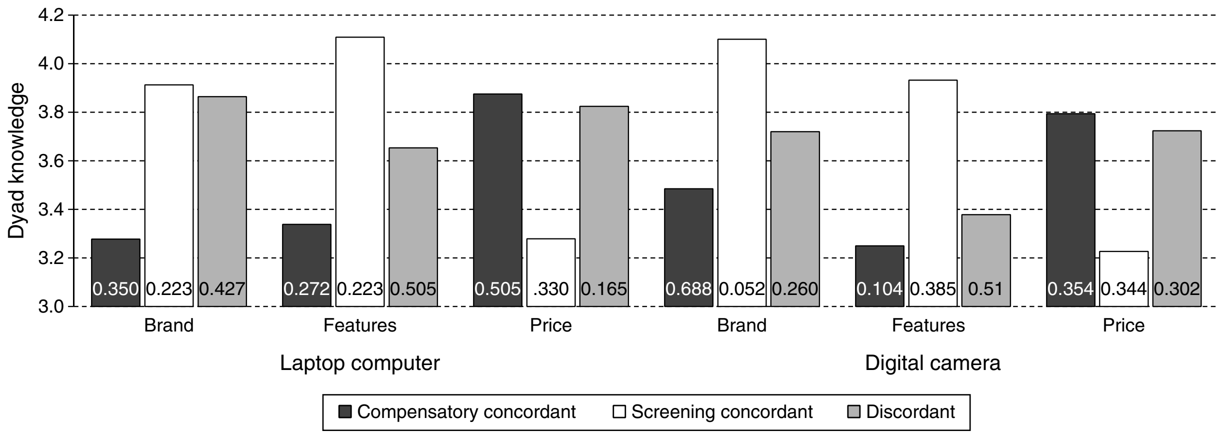
Table 4 reports the proportion of respondents that fall into one of the three stated can't-have, it-depends, and must-have attribute classification categories. The can't-have category indicates the attribute level would be screened out, whereas the must-have designation suggests that all attribute levels *except* this one would be screened out. To simplify exposition we discuss screening for three classes of attributes: brands, features, and price. Using the stated measures, we find that a sizable proportion of husbands would exclude either the Apple (33%) or the Gateway (29%) brands from consideration. On the opposite end of the spectrum, a small proportion of husbands (8%) would consider *only* the Apple brand. Screening based on product features is also prevalent—44.7% of husbands would exclude laptops without an Intel processor, and 33% would consider only quad-core laptops. We also see evidence of price screening in the market: 41.7% would exclude all laptops that exceed the \$799 price point. In comparing the digital camera data in Table 4 with the laptop computer data, there is far less brand screening, higher levels of features-based screening, and a similar type of price break point.

Looking at the wife-stated data across both product categories, we find that husbands and wives have a similar aggregate pattern of brand, feature, and price screening, but the action at the dyad level might be different. Using the stated attribute screening data from the two product categories and the DDP descriptions outlined in §2, we next classify dyads into CC, SC, and discordant groups for the brand, feature, and price attribute classes.[3] We examine the prevalence of the DDPs derived using these stated measures and link their existence to dyad characteristics, as is illustrated in Figure 1.

Across product categories and attribute classes, we find that each of the three DDP groups has a sizable presence in our data. Recall that the DPP grouping is conditional on both category and attribute class; thus the six sets of DDP group proportions reported in Figure 1 each sum to 1. Looking at these numbers, the

[3] Because we do not collect stated screening measures from dyads for the laptop computer and digital camera categories, we cannot distinguish expand from restrict within the discordant group using these data. Data from the flat-panel TV category do not have this limitation.

Figure 1 **Laptop and Camera Stated DDP Prevalence and Behavioral Explanation**



high proportion of discordant dyads for brand (0.427) and features (0.505) in the laptop computer category suggests that husbands and wives have very different consideration sets (i.e., the husband must have quad-core, but it depends for the wife). Compared across categories, there are far fewer discordant and screening concordant dyads for brand in the digital camera category largely because a very high percentage of dyads described camera brands in terms of it depends rather than can't have or must have. Next, we investigate factors that explain why dyads utilize different decision strategies.

Consistent with existing research that suggests expertise is linked to the use of choice heuristics (Bettman and Park 1980, Johnson and Russo 1984), Figure 1 shows that in both the laptop and digital camera categories, feature- and brand-based screening concordant dyads (i.e., the husband and wife both use screens) have higher product knowledge ($p < 0.05$) when compared with feature- and brand-based compensatory concordant dyads (i.e., the husband and wife both say it depends). This result suggests that more knowledgeable dyads are more likely to have smaller consideration sets because both parties agree to rule out specific brands or features. The opposite relationship between knowledge and screening emerges when looking at the price attribute in Figure 1—price-based screening concordant dyads have considerably lower product knowledge ($p < 0.05$) when compared with other groups. This means that the least knowledgeable dyads are most likely to form consideration sets on the basis of a price threshold.

Closely related measures of product knowledge such as experience, ownership, and advanced decision stage mimic these findings; thus we observe a general pattern of results over two product categories and multiple measures: more knowledgeable dyads tend to screen on brands and features, whereas less knowledgeable dyads screen on price.

4.2. Model-Based Inference (Flat-Panel TV)

In the preceding section, we used easily collected stated measures to identify compensatory concordant, screening concordant, and discordant groups for brand, feature, and price attribute classes. We show that dyad characteristics such as knowledge are drivers of screening behavior. In this section we report our findings from model-based inference on the conjoint choice data for the flat-panel television category as described in §3.2. These data complement our earlier findings in two ways. First, because we obtained joint choice data for the TV category, we are able to empirically investigate expand and restrict DDPs not studied earlier. Second, because stated measures may exhibit an upward bias in reported screening, we now rely on model-based inference. We also test a model that treats the stated screening data as prior information.

4.2.1. Model Comparison. Four different models were fit to these data. In addition to Models 1 and 2 proposed in §2, we also fit a dyadic compensatory model (Arora and Allenby 1999) that does not account for screening (Model 0). An alternative model specification that uses dyadic likelihood aggregation rather than a dyadic utility aggregation (Model 3) was also fit. In Model 3 the basic idea is that across a series of choices, the dyad chooses what the husband likes some times and what the wife likes other times. That is, the probability of alternative k' being chosen by a dyad d is a mixture of the husband h and the wife w choice probabilities. That is,

$$\begin{aligned}\Pr_d(y_{k'} = 1 \mid \beta_h, \beta_w, \tau_h, \tau_w) &= \psi_d \\ &\cdot \Pr_h(y_{k'} = 1 \mid \beta_h, \tau_h) + (1 - \psi_d) \\ &\cdot \Pr(y_{k'} = 1 \mid \beta_w, \tau_w), \qquad (14)\end{aligned}$$

where ψ_d is the probability that the dyad's choice is consistent with the husband's preference, and $(1 - \psi_d)$ is the probability that the dyad's choice is consistent with the wife's preference.

Table 5 Model Comparison

	Model 0	Model 1	Model 2	Model 3
	Dyadic compensatory	Dyadic consider-then-choose	Dyadic consider-then-choose with stated data as priors	Likelihood aggregation with stated data as priors
All dyads ($n=265$)				
DIC	10,380.020	8,712.203	8,313.273	10,184.640
In-sample hit rate	0.883	0.886	0.899	0.883
In-sample MAD	0.199	0.184	0.167	0.201
LMD	−4,234.351	−3,740.127	−3,494.958	−4,157.582
Holdout choice sets' hit rate	0.789	0.781	0.789	0.789
Holdout choice sets' MAD	0.261	0.261	0.251	0.283
Sample dyads ($n=200$)				
DIC	7,859.777	6,537.809	6,298.346	7,797.041
In-sample hit rate	0.883	0.893	0.904	0.883
In-sample MAD	0.195	0.177	0.168	0.205
LMD	−3,237.398	−2,802.254	−2,641.796	−3,192.334
Holdout choice sets' hit rate	0.790	0.780	0.808	0.795
Holdout choice sets' MAD	0.265	0.263	0.253	0.284
Holdout dyads ($n=65$)				
Hit rate	0.442	0.442	0.535	0.435
MAD	0.600	0.590	0.501	0.597

Model fit statistics are reported in Table 5. These include deviance information criterion (DIC; see Spiegelhalter et al. 2002), log marginal density (LMD; see Newton and Raftery 1994), hit rates, and mean absolute deviation (MAD). We begin with our findings reported in the top part of the table. For each model, for the full data set of 265 dyads we computed in-sample and out-of-sample fit statistics for each dyad. In-sample fit was based on 12 out of the total 14 choices, and the remaining 2 choices were used to obtain out-of-sample fit.

First, compared with Models 1 and 2, Model 3, which obtains dyadic choice probabilities via likelihood aggregation, does not perform well. This result is consistent with Arora and Allenby (1999) and suggests that the utility aggregation structure in Models 1 and 2 more flexibly accommodates polarization and attribute-specific compromise than does Model 3. Second, we find that noncompensatory consider-then-choose Models 1 and 2 outperform a compensatory Model 0. Finally, between the two consider-then-choose models, Model 2 (with stated data as priors) fits the data better than Model 1, thus highlighting the value of incorporating prior information in parameter estimation.

To assess the predictive power of the models, we also split the data into a calibration sample of 200 dyads and a holdout sample of 65 dyads. In the bottom part of Table 5, we report the fit statistics for the 200-dyad calibration sample and then use the hyperparameters from the calibration sample and the stated measures from the 65 holdout dyads to predict the choices for the holdout dyads. Hit rate and MAD statistics for this holdout sample demonstrate that accounting for screening improves the predictive power of the model and that leveraging stated data significantly enhances the model's ability to predict dyadic choices.

We note that although there is substantial improvement in the likelihood-based measures (e.g., DIC and LMD) when comparing Model 2 with Model 0, the improvement in hit rates is smaller. This happens because a noncompensatory model yields sharper choice probabilities by eliminating unacceptable alternatives, thus resulting in better LMD and DIC measures than a compensatory model if indeed there is screening in the decision process. At the same time, a compensatory model is sufficiently flexible to approximate a noncompensatory process by allowing coefficients to get very large or very small to capture for extreme preferences. A compensatory model therefore performs fairly well in identifying the most preferred alternative and has comparable hit rates as a noncompensatory model. This pattern of significant improvement in likelihood-based measures but less dramatic improvement in hit rates is consistent with results from prior research (Gilbride and Allenby 2004, 2006; Jedidi and Kohli 2005) that compare compensatory and noncompensatory models. It is, however, critical to recognize that beyond superior model fit, the bigger difference between the dyadic compensatory and noncompensatory models is that the latter allows us to uncover the DDP framework—the primary focus of this paper. A compensatory model fails to capture the richness of the DDP-based behavioral insights and their subsequent impact on managerial decisions.

Table 6 Noncompensatory Model (M2) Preference, Influence, and Screening Hyperparameters

	$\bar{\beta}_{\text{husband}}$	$\bar{\beta}_{\text{wife}}$	$\bar{\phi}$	$\bar{\tau}_{\text{husband}}$	$\bar{\tau}_{\text{wife}}$	$\bar{\tau}_{\text{dyad}}$
Sony	**0.290** (0.143)	**0.408** (0.154)	**0.756** (0.113)	0.041 (0.006)	0.049 (0.006)	0.042 (0.005)
Panasonic	0.087 (0.117)	0.072 (0.120)		0.075 (0.008)	0.076 (0.007)	0.076 (0.006)
Vizio	−0.118 (0.115)	−0.076 (0.138)		0.145 (0.005)	0.126 (0.005)	0.122 (0.004)
Samsung				0.054 (0.006)	0.041 (0.007)	0.045 (0.005)
Price	−**4.190** (0.286)	−**5.185** (0.367)	**0.148** (0.094)			
$1,299				0.171 (0.009)	0.190 (0.011)	0.180 (0.010)
$1,599				0.345 (0.014)	0.413 (0.017)	0.413 (0.017)
32" screen	−**2.324** (0.188)	−**2.049** (0.180)	0.418 (0.175)	0.165 (0.008)	0.167 (0.008)	0.220 (0.009)
42" screen	−**0.315** (0.150)	−**0.563** (0.142)		0.042 (0.005)	0.047 (0.005)	0.055 (0.006)
52" screen				0.034 (0.004)	0.034 (0.004)	0.033 (0.004)
Plasma	−**0.405** (0.143)	−0.175 (0.128)	0.731 (0.208)	0.076 (0.003)	0.100 (0.003)	0.117 (0.004)
720p resolution	−**1.731** (0.156)	−**1.554** (0.152)	**0.923** (0.211)	0.065 (0.003)	0.063 (0.002)	0.069 (0.003)
Standard warranty	−**0.418** (0.096)	−**0.428** (0.100)	0.740 (0.293)	0.000 (0.000)	0.004 (0.000)	0.000 (0.000)

Notes. Cells contain the posterior mean and standard deviation (in parentheses) of the hyperparameter. When the posterior mean is in bold, the 95% highest posterior density for that hyperparameter does not include 0 for preference and screening ($\bar{\beta}$ and $\bar{\tau}$) or does not include 0.5 for influence ($\bar{\phi}$).

Section 4.4 shows that a careful recognition of these DDPs has substantive implications for pricing and product design decisions that a compensatory model fails to capture.

4.2.2. Insights from Model Parameter Estimates. The aggregate-level or hyperparameter estimates from Model 2 (reported in Table 6) indicate that features and price play a more important role than brands in husbands' and wives' choices. In particular, attribute sensitivity ($\bar{\beta}$) is high for price, screen size, and resolution, but it is quite low for brand. Overall, wives ($\bar{\beta}_{\text{wife}}$) show the same preference pattern as husbands, although wives appear to be slightly more sensitive to price and less sensitive to high-end product features. In interpreting the influence parameter ($\bar{\phi}$), recall that $\bar{\phi} = 0.5$ suggests equal influence between husband and wife. For some features (e.g., 720p resolution) we find that husbands have a higher influence ($\bar{\phi} > 0.5$, probability > 0.95) than wives. Wives, in contrast, have a higher aggregate influence ($\bar{\phi} < 0.5$, probability > 0.95) than husbands on price.

Because this paper's emphasis is on the consideration aspect of the consider-then-choose model, we focus our attention on the screening parameter estimates for husbands, wives, and dyads. The aggregate results show that Vizio is a brand that would be excluded from a sizable proportion of husband (14.5%), wife (12.6%), and dyad (12.2%) consideration sets. Similar to the results from laptop computers and digital cameras, we also see evidence of price thresholds—a large proportion of dyads (41.3%) exclude alternatives offered at the highest ($1,599) price point. On average, the husbands screen out high-price televisions less than the wives, a pattern that is consistent with the price sensitivity ($\bar{\beta}$) differences between the two groups.

Although the overall proportion of attribute-level screening recovered by the model is modest, comparing these estimates with the stated can't-have data reveals that the latter are significantly exaggerated. For example, over half the dyads (52.5%) stated they would not consider alternatives with 720p resolution, yet when making choices in a trade-off environment, the model shows that 11.7% of dyads actually exclude 720p resolution alternatives from consideration. The stated and recovered consideration proportions displayed in Figure 2 illustrate that the problem of stated data screening exaggeration (upward bias) exists across most attributes in the study. Although stated measures may not be an accurate reflection of consideration alone, the comparison between Models 1 and 2 in Figure 2 shows the value of incorporating these stated measures as priors in a model. Incorporating stated data as priors in the dyadic consider-then-choose model therefore offers a reasonable in-between approach.

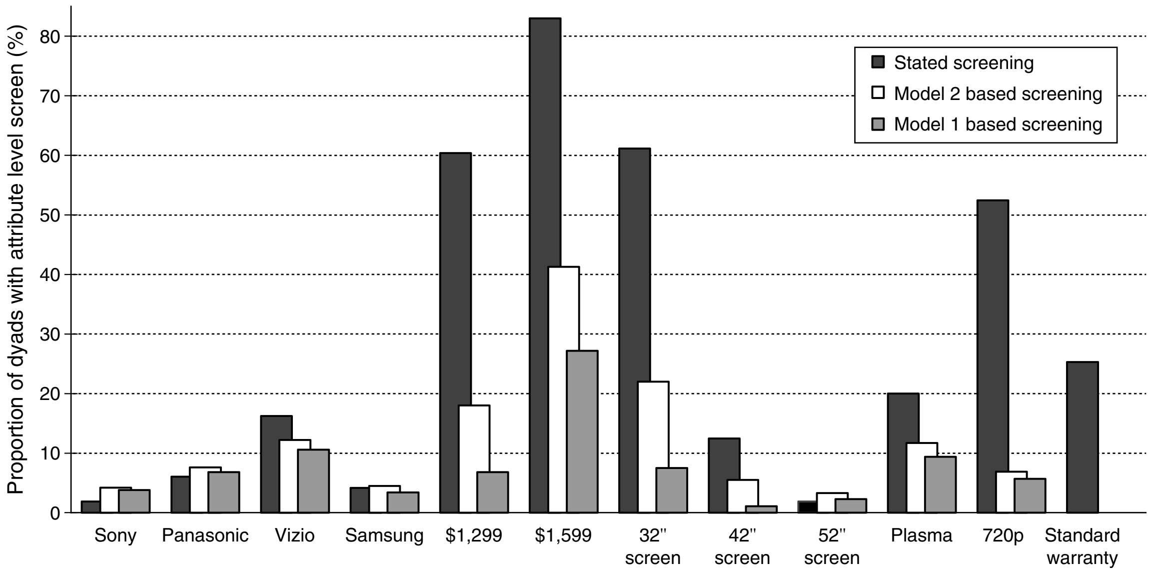
Next, we link the model-based screening parameters with the proposed DDP framework to empirically investigate their effect on decision quality and efficiency for buyers.

4.3. DDP Incidence and Implications for Buyers

We construct the DDPs as outlined in §2.3 for each of the three attribute classes using the dyad-level, model-based screening parameters from Model 2. The posterior incidence of these DDPs, as well as their relationship to stated and model-based measures, is reported in Table 7. As reported in the first column of this table, the most prevalent DDP across the brand (69.3%), feature (57.1%), and price (44.7%) attribute classes is the compensatory concordant DDP. Screening concordant, expand, and restrict DDPs are also well represented in the data.[4] For example, the

[4] Within an attribute class, the incidence of mixed DDP is too small to draw meaningful comparisons. Therefore we do not include it in this section. Across attributes, the mixed DDP bin is larger and is included in subsequent analyses.

Figure 2 Comparison of Stated Screening with Model-Based Screening Estimates



expand (25%) and screening concordant DDP groups (19.8%) for price are sizable. Next, we focus on two comparisons with decision quality implications for buyers: (i) When concordant, do compensatory concordant dyads make better decisions than screening concordant dyads? And (ii) when discordant, does an expand or restrict strategy result in better decisions? We also contrast decision efficiency of alternative DDPs.

4.3.1. Screening Concordance Is Better Than Compensatory Concordance. Table 7 also shows that across all three attribute classes, screening concordant dyads, with their smaller consideration sets, make quicker choice decisions than compensatory concordant dyads (probability > 0.95). This decision speed result is differentially linked to dyad characteristics such as product experience. Dyads defined as screening concordant on the basis of the brand and feature

Table 7 Incidence and Implications of Model-Based DDPs for Each Attribute Class

	Proportion	Product experience	Joint task time (min)	Choice concession	Choice inefficiency	Preference intensity
Brand						
Compensatory concordant	0.693 (0.017)	3.012 (0.019)	5.547 (0.204)	0.375 (0.009)	0.049 (0.003)	0.837 (0.005)
Screening concordant	0.090 (0.007)	3.318 (0.082)[a]	4.280 (0.216)[a]	0.354 (0.031)	0.049 (0.009)	0.834 (0.017)
Expand	0.130 (0.016)	2.774 (0.102)	4.918 (0.509)	0.575 (0.029)	0.070 (0.009)	0.781 (0.017)
Restrict	0.087 (0.008)	3.088 (0.090)[b]	3.720 (0.125)[b]	0.443 (0.029)[b]	0.041 (0.008)[b]	0.876 (0.015)[b]
Features						
Compensatory concordant	0.571 (0.011)	2.949 (0.019)	5.555 (0.030)	0.421 (0.011)	0.058 (0.003)	0.814 (0.005)
Screening concordant	0.174 (0.006)	3.261 (0.030)[a]	4.628 (0.103)[a]	0.293 (0.016)[a]	0.041 (0.005)[a]	0.867 (0.008)[a]
Expand	0.116 (0.010)	3.087 (0.094)	4.867 (0.211)	0.498 (0.025)	0.063 (0.008)	0.788 (0.014)
Restrict	0.140 (0.010)	2.925 (0.083)	4.691 (0.117)	0.401 (0.021)[b]	0.026 (0.005)	0.908 (0.010)[b]
Price						
Compensatory concordant	0.447 (0.015)	3.237 (0.026)	5.378 (0.223)	0.390 (0.013)	0.053 (0.003)	0.822 (0.006)
Screening concordant	0.198 (0.015)	2.691 (0.068)[a]	4.617 (0.195)[a]	0.310 (0.022)[a]	0.041 (0.005)	0.868 (0.009)[a]
Expand	0.250 (0.020)	2.960 (0.066)	5.475 (0.435)	0.498 (0.022)	0.056 (0.005)	0.820 (0.010)
Restrict	0.105 (0.015)	2.814 (0.127)	4.832 (0.388)	0.431 (0.035)	0.049 (0.009)	0.844 (0.017)

Note. Cells contain posterior mean and standard deviation (in parentheses) of the measure by group.
[a]Screening concordant significantly different (probability > 0.95) from compensatory concordant.
[b]Restrict significantly different (probability > 0.95) from expand.

attributes are more experienced than their counterpart compensatory concordant dyads (probability > 0.95). The opposite is true of dyads defined as screening concordant for price—they have less experience than compensatory concordant dyads (probability > 0.95). The consistent pattern is that less informed dyads tend to take decision-making shortcuts based on price. Regardless of the motivation for having smaller consideration sets, we find that screening concordant dyads make less choice concession, have lower choice inefficiency, and experience higher dyadic preference intensity. We therefore conclude that screening concordant dyads make quicker as well as better dyadic decisions when compared with compensatory concordant dyads.

4.3.2. Restrict Is Better Than Expand. The second DDP contrast of interest applies to discordant dyads: expand versus restrict. We have learned that dyads with smaller consideration sets have less information to process in making a decision. As such, in Table 7 we find that the restrict dyads (smaller consideration set) make quicker choice decisions compared with expand dyads (larger consideration set). To illustrate, discordant dyads on brand who restrict their consideration set complete the joint choice task over a minute earlier (3.720 minutes) than other brand discordant dyads who expand their consideration set (4.918 minutes, probability > 0.95). The restrict DDP is related to product expertise—brand restrict dyads have more product experience (3.088) than brand expand dyads (2.774, probability > 0.95). In addition, the restrict dyads exhibit lower concession, lower choice inefficiency, and higher dyadic preference intensity. We therefore conclude that restrict dyads make quicker as well as better dyadic decisions than expand dyads.

4.3.3. Mixed DDP Benefits from Smaller Consideration Sets. The key distinction between expand and restrict is the dyad's retention or abandonment of a particular dyad member's smaller consideration set. The mixed strategy has both expand and restrict DDP characteristics. To assess how well a mixed strategy works, we aggregate across the attributes in all three classes to form a single DDP classification that has a large enough proportion of the mixed DDP group (6%). Choice concession for the mixed DDP (0.497) is similar to the expand DDP (0.491) and different from the restrict DDP (0.384, probability > 0.95). In contrast, inefficiency and preference intensity for the mixed DDP (0.034 and 0.886) are similar to the restrict DDP (0.037 and 0.877) and different from the expand DDP (0.063, probability > 0.95; and 0.795, probability > 0.95). These results suggest that the mixed DDP strategy also benefits from narrowing of alternatives.

4.3.4. Screening Concordant Dyads Have Lower Regret. Overall, the pattern of results suggests that dyads with smaller consideration sets end up with better decisions. The data from the joint shopping task (see §3.4) provide the opportunity to assess the usefulness of the screening decision strategy in a context outside of the conjoint choice task. The results from that shopping task indicate that smaller consideration sets do lead to better dyadic decisions. Compared with compensatory concordant dyads, screening concordant dyads take fewer shopping task trips (4.330 versus 3.463, probability > 0.95), exhibit higher shopping task dyadic preference intensity (0.534 versus 0.740, probability > 0.95), perceive they compromised less (0.459 versus 0.255, probability > 0.95), and indicate lower postshopping task regret[5] (0.340 versus −0.150, probability > 0.95). The finding that fewer options leads to lower regret links nicely with existing overchoice research (e.g., Schwartz 2004).

4.4. Substantive Implications of a Dyadic Consider-Then-Choose Model

So far we have tested the dyadic noncompensatory choice model, and we empirically investigated the prevalence of alternative dyadic decision processes and their impact on decision efficiency and quality. Next, we investigate the substantive implications of the dyadic noncompensatory model on managerial decisions involving product design and pricing. We begin with the observation that unaccounted-for price thresholds in a compensatory model bias the aggregate price sensitivity estimates upward. That is, aggregate price coefficients in a compensatory model tend to be more negative to capture exclusion of high-price alternatives (e.g., $\bar{\beta}_{\text{price husband M2}} = -4.190$ versus $\bar{\beta}_{\text{price husband M0}} = -4.454$). A similar argument also applies to nonprice attributes as preference estimates in a compensatory model attempt to account for attribute screening. Next, we illustrate substantive implications of such systematic differences in parameter estimates of dyadic noncompensatory and compensatory models. We conduct an optimal product profile and pricing exercise for flat-panel televisions and compare the managerial guidance from our dyadic consider-then-choose model relative to a compensatory model. The results show that the models yield starkly different substantive results.

We conduct a stylized market simulation at the dyad level starting with a baseline scenario with three alternatives as shown in Table 8. For each

[5] Regret was measured using individual postshopping task responses to statements such as "I regret our decision" and "I think we made a mistake" and was then aggregated to the dyad level as a dyadic regret factor score. Perceived compromise is also a stated measure of the shopping task decision process, where 0 indicates that both dyad members felt that "no compromise was needed."

Table 8 Simulated Product Profile Market Share in Two Scenarios

Baseline scenario		Sony, 32", LCD, 1080p, extended, \$899	Panasonic, 42", plasma, 720p, standard, \$899	Vizio, 32", LCD, 1080p, standard, \$699	No-buy
Market share					
Consider-then-choose model (Model 2)	Husband	0.329	0.333	0.285	0.053[b]
	Wife	0.326	0.283[a]	0.340[a]	0.051[b]
	Dyad	0.275	0.334	0.322	0.069[b]
Compensatory model (Model 0)	Husband	0.340	0.350	0.310	0.000
	Wife	0.333	0.298[a]	0.368[a]	0.000
	Dyad	0.317	0.330	0.353	0.000

Introduce 52" profile		Sony, 32", LCD, 1080p, extended, \$899	Panasonic, 42", plasma, 720p, standard, \$899	Vizio, 32", LCD, 1080p, standard, \$699	Samsung, 52", LCD, 1080p, extended, \$1,249	No-buy
Market share						
Consider-then-choose model (Model 2)	Husband	0.137	0.201	0.206	0.457[b]	0.000
	Wife	0.172	0.151[a]	0.267[a]	0.410[a,b]	0.000
	Dyad	0.113	0.191	0.242	0.454[b]	0.000
Compensatory Model (Model 0)	Husband	0.150	0.229	0.235	0.386	0.000
	Wife	0.170	0.181[a]	0.296[a]	0.353	0.000
	Dyad	0.136	0.203	0.268	0.392	0.000

[a]Difference between husband and wife does not include 0 over 90% highest probability density.
[b]Difference between Model 0 and Model 2 does not include 0 over 90% highest probability density.

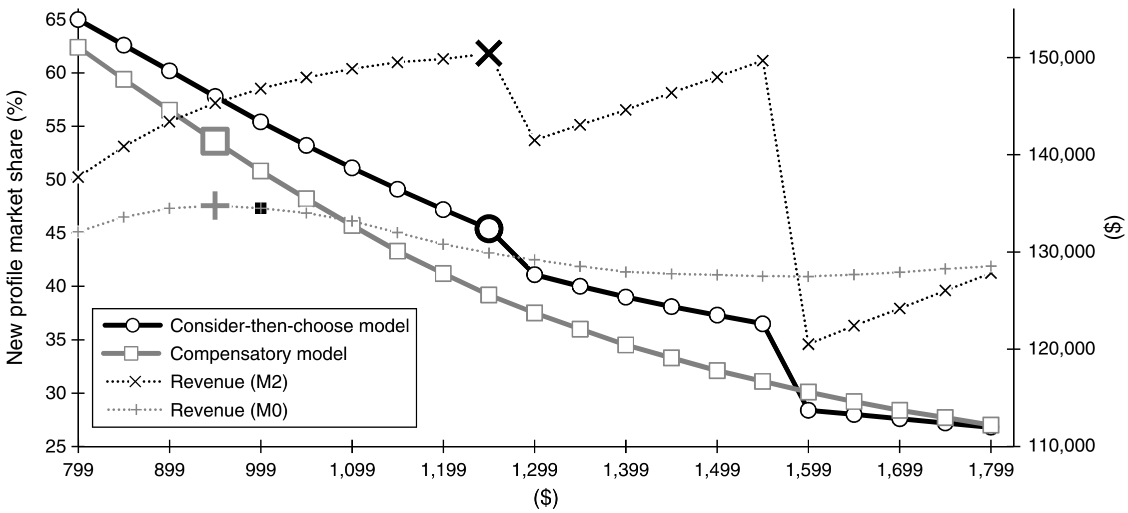
decision maker, under both the compensatory model (Model 0) and the dyadic consider-then-choose model (Model 2), we obtain the posterior distribution of choice probabilities and functions of the parameters such as market share and willingness to pay. The three alternatives in the baseline scenario each claim a roughly equal proportion of the simulated market. Owing to preference structure disparities as previously shown in §4.2, there are differences between husbands and wives as to which product is most preferred—the husbands prefer a larger, more expensive TV relative to the wives. There are large discrepancies in market share predictions when using model parameters of either husbands or wives, strongly supporting the need for a dyadic choice model. The husband–wife differences are manifest for both compensatory and consider-then-choose models. Next, we contrast the findings from the two models by focusing on results corresponding to the dyad choices.

4.4.1. Because of Screening, the Market Is Not Cleared. One thing we learn from the consider-then-choose model that the standard compensatory model cannot tell us is that given the baseline set of offerings, the market does not clear. That is, husbands/wives/dyads who exclude all three alternatives from consideration exist. This is shown in Table 8 as the "No-buy" proportion. This means some dyads would not buy any of the three options because the alternatives do not fall in their consideration set. In this particular situation, there is a small proportion of dyads who must have a large 52" television and, as such, would not choose any of the existing offerings. Because the compensatory model does not account for the consideration stage of the decision, it would ascribe choice to the most attractive of the three smaller screen size alternatives rather than ruling them all out, thus overstating its demand.

Motivated by this unmet market need for large TVs that the consideration model uncovers, we construct a scenario that includes a fourth option with a 52" screen. To find this fourth option, we search the design space for the optimal combination of binary product attributes to accompany a 52" Samsung brand TV. To determine the optimal price for the new product, we search between \$799 and \$1,799 in \$50 increments for the price level that maximizes new product revenue. This new product profile and the corresponding scenario of market shares are shown in the bottom panel of Table 8.

4.4.2. The New Product Optimal Prices and Demand Forecasts Are Different. The two models make very different predictions regarding the optimal price and market demand for the proposed new product. Figure 3 illustrates these differences by showing the posterior mean of simulated market share and revenue at each of the price points in the search space under the dyadic compensatory model (Model 0) and the consider-then-choose model (Model 2). The optimal price point for the new profile as determined under each model is denoted by an enlarged plotting symbol. These optima are not the same. The compensatory model predicts an optimal price of \$949 (just higher than the existing products in the market), whereas the consider-then-choose model suggests an

Figure 3 New Profile Market Share and Revenue at Various Prices Under Two Different Models



optimal profile price of \$1,249—a price \$300 higher. If a manager set prices according to the compensatory model optimum (\$949) and ignored the additional information the consider-then-choose model provides, market share for the new product would be higher, but revenue would be 3.5% lower than if the new product were priced at the optimum (\$1,249) indicated by the consideration-based model. Furthermore, even at the same price point (i.e., \$1,249), the compensatory model underestimates demand relative to the forecast obtained from the consider-then-choose model. The higher aggregate price sensitivity of a compensatory model explains this pattern of results in our illustration. In general, we see that the ability of a noncompensatory model to pick up this behavioral richness has direct substantive implications that should not be ignored.

Attribute-specific willingness to pay ($\beta_{\text{attribute}}/\beta_{\text{price}}$; see Meijer and Rouwendal 2006), an interrelated dimension of product design and pricing, is also affected by the presence of screening. Once again, because β_{price} for the two models differs, so does the willingness-to-pay (WTP) measure. As an illustration, we examined each dyad's willingness to pay to move from a 32" screen size to a 52" screen size. For a dyadic compensatory model, the $\text{WTP}_{52''}$ is \$424 compared to \$372 for a noncompensatory model. It is important to recognize that the latter WTP is an average for both screeners and nonscreeners in the sample. To dig a bit deeper, we find that $\text{WTP}_{52''}$ for dyads who would screen high-priced alternatives is significantly lower ($\text{WTP}_{52''} = \$181$) compared with dyads who would not screen high-priced alternatives ($\text{WTP}_{52''} = \$440$, probability > 0.95). Not surprisingly, the screening–WTP relationship works in the opposite direction when consideration is attribute based. For example, WTP for a 52" screen size is much higher among dyads who exclude a 32" screen size from consideration ($\text{WTP}_{52''} = \$556$) compared with those who would not ($\text{WTP}_{52''} = \$315$, probability > 0.95). The lesson from this simple WTP illustration is an important one. Pricing decisions that ignore dyadic screens fail to accurately characterize how WTP varies in the marketplace. As shown earlier in this section, this can result in setting a suboptimal price and predicting a demand schedule that is inaccurate. As such, a meaningful advantage of a consider-then-choose model is its ability to capture discontinuities in the demand schedule that naturally arise because of price screening thresholds.

5. Model Extensions

This paper demonstrates that noncompensatory dyadic decision processes are conceptually rich and substantively important. Before we conclude, we outline some model extensions that suggest the logical next steps. In particular, we focus on two aspects for model extension: how the cost of thinking may factor into screening and the strategic use of consideration sets. The former attempts to explain differential dyadic screening in the marketplace because of thinking costs dyads are willing to incur, and the latter assumes that a member's screening behavior may be influenced by the others' in a systematic way. A key distinction between a dyadic application of an attribute screening consider-then-choose model and a cost-of-thinking approach is the implied mechanism for the dyadic decision process. A cost-of-thinking model would specify how the husband-and-wife cognitive cost parameters get aggregated rather than how the attribute-level screens and consideration sets are integrated. Furthermore, although our data collection procedure ruled out the possibility of strategic consideration by explicitly directing individuals to choose for themselves at the individual stage, the issue of strategic consideration is an aspect of joint choice decision making that merits further investigation. We next outline a model that can be used to capture such strategic consideration building on a cost-of-thinking model.[6]

For a given person, an attribute level m is screened out ($\tau_m = 1$) if the expected gain G_m from including the attribute level is less than the cost-of-thinking γ (Gilbride and Allenby 2006). Let the subscripts h, w, and d represent husband, wife, and dyad, respectively. Then $\tau_{hm} = 1$ if $G_{hm} < \gamma_h$, $\tau_{wm} = 1$ if $G_{wm} < \gamma_w$, and $\tau_{dm} = 1$ if $G_{dm} < \gamma_d$. To capture a husband's strategic consideration based on the knowledge of the other spouse's screening behavior, the expected gain for the husband is

$$G_{hm} = E_x\big[E_{\varepsilon_h}[\max(X\beta_h + \eta_{hm}\mathrm{I}_{\{\tau_{wm}=1\}} + \varepsilon_h) - \max(X_{-m}\beta_h + \varepsilon_h)]\big], \quad (15)$$

where X_{-m} denotes the matrix that captures the choice alternatives without the attribute level m, η_{hm} captures the influence of the wife's decision on the husband's, and $\mathrm{I}_{\{\cdot\}}$ is an indicator function. If η_{hm} is positive, then the attribute level is more likely to be included for consideration by the husband based on the knowledge that it is excluded for consideration by the wife. On the other hand, if η_{hm} is negative, then the attribute is more likely to be excluded. A similar argument applies for the wife's gain function (G_{wm}). The expected gain for the dyad is given by

$$G_{dm} = E_x\big[E_{\varepsilon_d}[\max(X\beta_d + \varepsilon_d) - \max(X_{-m}\beta_d + \varepsilon_d)]\big], \quad (16)$$

where the dyad's joint preference β_{dm} on attribute level m is linked to the individual preferences through the influence parameter ϕ_{hm} as

$$\beta_{dm} = \phi_{hm}(\beta_{hm} + \eta_{hm}\mathrm{I}_{\{\tau_{wm}=1\}}) + (1 - \phi_{hm}) \cdot(\beta_{wm} + \eta_{wm}\mathrm{I}_{\{\tau_{hm}=1\}}). \quad (17)$$

Next, let G_{hm0} be the husband's expected gain from including attribute level m knowing that the wife is including it for consideration ($\tau_{wm} = 0$), and let G_{hm1} be the expected gain knowing that the wife is screening it out ($\tau_{wm} = 1$). Similarly, the wife's expected gains are G_{wm0} and G_{wm1}. The dyad's expected gains are G_{dm00}, G_{dm01}, G_{dm10}, and G_{dm11}, corresponding respectively to the individual members' screening behavior $(0, 0)$, $(0, 1)$, $(1, 0)$, and $(1, 1)$. There are a total of eight possible solutions for the screening indicators $(\tau_{hm}, \tau_{wm}, \tau_{dm})$, and the equilibrium conditions are

$$\begin{array}{ll}
(0,0,0) & \text{if } G_{hm0} > \gamma_h,\ G_{wm0} > \gamma_w,\ \text{and } G_{dm00} > \gamma_d;\\
(0,0,1) & \text{if } G_{hm0} > \gamma_h,\ G_{wm0} > \gamma_w,\ \text{and } G_{dm00} < \gamma_d;\\
(0,1,0) & \text{if } G_{hm1} > \gamma_h,\ G_{wm0} < \gamma_w,\ \text{and } G_{dm01} > \gamma_d;\\
(0,1,1) & \text{if } G_{hm1} > \gamma_h,\ G_{wm0} < \gamma_w,\ \text{and } G_{dm01} < \gamma_d;\\
(1,0,0) & \text{if } G_{hm0} < \gamma_h,\ G_{wm1} > \gamma_w,\ \text{and } G_{dm10} > \gamma_d;\\
(1,0,1) & \text{if } G_{hm0} < \gamma_h,\ G_{wm1} > \gamma_w,\ \text{and } G_{dm10} < \gamma_d;\\
(1,1,0) & \text{if } G_{hm1} < \gamma_h,\ G_{wm1} < \gamma_w,\ \text{and } G_{dm11} > \gamma_d;\\
(1,1,1) & \text{if } G_{hm1} < \gamma_h,\ G_{wm1} < \gamma_w,\ \text{and } G_{dm11} < \gamma_d.
\end{array}$$

To address the problem of multiple equilibria that may exist in certain conditions (e.g., Hartmann 2010), we select the equilibrium that gives maximum total gain—that is, the one that maximizes $G_{hm} + G_{wm} + G_{dm}$.

6. Discussion

Anecdotal evidence for choice decisions made by families (e.g., buying a house) and organizations (e.g., hiring decisions) suggests that groups often exclude alternatives from consideration based on a wide variety of factors. This paper fills a void in the literature by capturing the intersection of member-level consideration sets in a dyadic consider-then-choose model. The DDP framework we introduce facilitates the investigation of both the compensatory and noncompensatory dimensions of a joint choice decision. We investigate alternative ways in which consideration set differences between members are reconciled and the subsequent implications for decision efficiency and quality.

6.1. What We Find

Across a variety of attribute classes (e.g., brands, features, and price), we find that there are sizable proportions of dyads who adopt a concordant (compensatory or noncompensatory) or a discordant (expand, restrict, or mixed) decision process. With regard to the consideration stage of the decision process, more knowledgeable dyads tend to screen on brands and features, whereas less knowledgeable dyads screen on price. We find that the stated measures of screening behavior are biased upward but serve an excellent role as prior information in a statistical model of dyadic choice. Model-based inference in our empirical investigation shows that compared with compensatory dyads, dyads with smaller consideration sets make quicker and better decisions. Specifically, when comparing compensatory concordant dyads to screening concordant dyads and expand dyads to restrict dyads, those that use screening not only make quicker decisions but are also better off.

[6] We thank the associate editor for this suggestion.

6.2. Implications for Buyers

One message to a dyad or group making collective choice decisions is that knowledge is the critical first step of joint choice. Greater knowledge likely results in the exclusion of alternatives, thus setting the stage for quicker, better decisions. At the level of a dyad, agreeing on what to exclude from consideration helps make better decisions. If the members do not a priori agree on which alternatives to exclude, our empirical evidence suggests that consideration set restriction is a significantly better decision process than set expansion. Although the concept of dyadic fairness might prima facie implicate an expand strategy, restricting the consideration set by leveraging one group member's screening thresholds leads to improved welfare and decision efficiency.

6.3. Implications for Sellers

Our findings speak to at least two marketing constituencies: sales and product design. Product returns attributable to buyer's remorse represent a significant cost to retailers and manufacturers ($3.7 billion for consumer electronics; see Lawton 2008), but a seller's efforts to maximize buyer welfare can be challenging in a dyadic decision context. Our research suggests that there are some dyadic decision processes—*screening when concordant or restrict when discordant*—that help make quicker and better decisions. When carefully used in the selling process, these strategies can become an effective tool to maximize a dyad's overall happiness with the decision. Because we find that less knowledgeable dyads screen more on price, a price-restricted consideration set may signal an opportunity for a Best Buy salesperson, for example, to educate the dyad about the product and, in so doing, maximize dyadic welfare.

We find that preference differences between decision makers and careful recognition of dyadic screening behavior can substantially affect product design and pricing decisions. Product decisions that ignore attribute-level consideration will likely underestimate demand for a new functionally superior product and could possibly underprice the new offering, particularly if price-based screening thresholds are prevalent. Results from the optimal product profile and pricing exercise demonstrate that there might be a real cost to ignoring screening. In sum, our framework to capture the dyadic consideration dimension of the choice process yields insights that are conceptually novel and substantively relevant.

6.4. Directions for Future Research and Limitations

We conclude by noting some limitations of our data. First, although the decision to use only married couples is representative of a certain type of dyad in the marketplace, our data may underestimate the level of discord when compared to studies that use other types of dyads (e.g., organization buyers). Although collecting data from such dyads is time consuming and expensive, it would be instructive to expand this enquiry to business-to-business settings. As an example, although our sample size is large relative to other studies of group decision making, we were somewhat constrained by the sample size of some of the DDPs (i.e., mixed). Contexts that involve higher discord may help overcome this limitation. Second, although we find no systematic differences in responses from groups that completed one or two product categories, the overall length of our survey was long. This may have adversely affected data quality from the joint shopping task near the end of the survey, where dyads engaged in limited search and frequently bought from the first store they visited. This suggests that future research in this area should restrict data to fewer categories and limit the number of questions to the extent possible. Alternative methodologies that bypass the need to collect dyadic data (e.g., Aribarg et al. 2010) should also be explored. Finally, the dyadic decision process framework we propose naturally extends to a group with greater than two members. For example, key conceptual ideas pertaining to concordant (noncompensatory or screening) and discordant (expand, restrict, or mixed) decision processes also apply to larger groups. Correspondingly, the model could be extended to a larger group by increasing the dimension of preference (β), influence (ϕ), and screening (ω) parameters. Empirical testing of such a model, however, presents significant challenges because such data are not readily available. Future research should investigate such model extensions to larger groups.

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Appendix. Estimation Algorithm

The following Markov chain Monte Carlo algorithm was used to obtain the posterior estimates of the model parameters.

(1) Generate $\theta_d = [\beta_{dh}, \beta_{dw}, \phi_d]$.

For a given dyad d, let vector $c_d = [k^{dh}, k^{dw}, k^d]$ denote the vector of the husband's, wife's, and the dyad's chosen alternatives; that is, $y_{k^{dh}} = 1, y_{k^{dw}} = 1$, and $y_{k^d} = 1$. The full conditional distribution of θ_d is

$$\begin{aligned} &f(\theta_d \mid c_d, \omega_d, \bar{\theta}, D) \\ &\quad \propto f(k_d \mid \theta_d, \omega_d) \times f(\theta_d \mid \bar{\theta}, D) \propto \Pr_{dh}(k_{dh}) \times \Pr_{dw}(k_{dw}) \\ &\quad \times \Pr_d(k_d) \times \exp\left[-\tfrac{1}{2}(\theta_d - \bar{\theta})' D^{-1}(\theta_d - \bar{\theta})\right], \end{aligned} \tag{18}$$

where $\Pr_{dh}(k_{dh})$, $\Pr_{dw}(k_{dw})$, and $\Pr_d(k_d)$ are obtained through Equations (2)–(4). A random-walk Metropolis–Hastings step is used to generate θ_d separately for each dyad d. Let $\theta_d^* = \theta_d + s \times \mathrm{N}(0, I)$ represent the proposed candidate new draw, and let θ_d represent the current draw. Let $LP(\theta_d)$ denote the last expression in (18). Accept θ_d^* with probability $= \min(LP(\theta_d^*)/LP(\theta_d), 1)$.

(2) Generate $\omega_d = [\tau_{dh}, \tau_{dw}, \tau_d]$.

For a given dyad d, we follow Gilbride and Allenby (2004, 2006) and use "Griddy Gibbs" to draw ω_{dm} sequentially, given $\omega_{dm'}$ on all other attribute levels m'. There are eight (2^3) possible realizations of the ω_{dm} vector of 0s and 1s, which we denote by w^b, $b = 1, \ldots, 8$. First, we define for each w^b

$$L_d(w^b) = f(c_d \mid \theta_d, \omega_{dm} = w^b, \omega_{dm', m' \neq m}) = \begin{cases} 0, & \text{if contradiction;} \\ \Pr_{dh}(k_{dh}) \times \Pr_{dw}(k_{dw}) \times \Pr_d(k_d), & \\ \quad \text{otherwise.} \end{cases}$$

"Contradiction" represents the scenario when the proposed w^b contradicts observed choices, that is, when w^b indicates that alternative k is screened out, but, in fact, it is chosen. $\Pr_{dh}(k_{dh})$, $\Pr_{dw}(k_{dw})$, and $\Pr_d(k_d)$ are obtained through Equations (2)–(4) by assuming $\omega_{dm} = w^b$ given all other $\omega_{dm'}$s. Next, out of all eight possible w^bs, select one w^{b^*} with probability

$$\frac{L_d(w^{b^*}) \times p_{b^*m}}{\sum_{b=1}^{8} L_d(w^b) \times p_{bm}} \quad \text{for Model 1,} \quad \text{or}$$

$$\frac{L_d(w^{b^*}) \times p_{db^*m}}{\sum_{b=1}^{8} L_d(w^b) \times p_{dbm}} \quad \text{for Model 2,}$$

where p_{dbm}, $b = 1, \ldots, 8$, are the multinomial probabilities for the eight versions of the ω_{dm} vector.

(3) Generate $\bar{\theta}$ from a multivariate Normal (MVN) distribution as

$$\begin{aligned} f(\bar{\theta} \mid \{\theta_d\}, D) &\propto \prod_{d=1}^{n} f(\theta_d \mid \bar{\theta}, D) \times f(\bar{\theta}) \\ &\propto \exp \sum_{d=1}^{n} \left[-\tfrac{1}{2}(\theta_d - \bar{\theta})' D^{-1} (\theta_d - \bar{\theta}) \right] \\ &\quad \times \exp\left[-\tfrac{1}{2}(\bar{\theta} - \delta)' A^{-1} (\bar{\theta} - \delta) \right] \\ &\sim \mathrm{MVN}\left((nD^{-1} + A^{-1})^{-1} \left(\sum_{d=1}^{n} D^{-1}\theta_d + A^{-1}\delta \right), \right. \\ &\qquad \left. (nD^{-1} + A^{-1})^{-1} \right), \end{aligned}$$

where the prior distribution of $\bar{\theta}$ is assumed to be multivariate Normal with mean δ and covariance matrix A. In our estimation, we use a diffuse prior, where $\delta = 0$ and $A = 100\mathrm{I}$.

(4) Generate D from an Inverted Wishart distribution as

$$\begin{aligned} & f(D \mid \{\theta_d\}, \bar{\theta}) \\ &\quad \propto \prod_{d=1}^{n} f(\theta_d \mid \bar{\theta}, D) \times f(D) \\ &\quad \propto |D|^{-n/2} \exp \sum_{d=1}^{n} \left[-\tfrac{1}{2}(\theta_d - \bar{\theta})' D^{-1} (\theta_d - \bar{\theta}) \right] \\ &\qquad \times |D|^{-(v+q+1)/2} \exp\left[-\tfrac{1}{2} \mathrm{Trace}(D^{-1} V) \right] \\ &\quad \sim \text{Inverted Wishart}\left(n + v, \sum_{d=1}^{n} (\theta_d - \bar{\theta})(\theta_d - \bar{\theta})' + V \right), \end{aligned}$$

where q is the length of vector θ_d. The prior distribution of D is assumed to be Inverted Wishart(v, V). In our estimation, we set $v = q + 1$, and $V =$ identity matrix of size q.

(5a) Generate $[p_{1m}, \ldots, p_{7m}]$ for Model 1 from a generalized Dirichlet as

$$\begin{aligned} & f([p_{1m}, \ldots, p_{7m}] \mid \{\omega_{dm}\}) \\ &\quad \propto \prod_{d=1}^{n} f(\omega_{dm} \mid [p_{1m}, \ldots, p_{7m}]) \times f([p_{1m}, \ldots, p_{7m}]) \\ &\quad \sim \text{generalized Dirichlet}(\eta_m + \alpha, \eta_m + \zeta), \end{aligned}$$

and $p_{8m} = 1 - p_{1m} - \cdots - p_{7m}$. For a given attribute level m, $[p_{1m}, \ldots, p_{7m}]$ is drawn from a generalized Dirichlet$(\eta_m + \alpha, \eta_m + \zeta)$ distribution with a generalized Dirichlet(α, ζ) prior, where $\alpha = 1$ and $\zeta = [7, 6, 5, 4, 3, 2, 1]$, and $\eta_m = (\eta_{1m}, \ldots, \eta_{8m})$ is a vector of counts where $\eta_{bm} = \sum_{d=1}^{n} 1_{\{\omega_{dm} = w^b\}}$ is the count of the dyads that have used decision process strategy b for $b = 1, \ldots, 8$.

(5b) Generate $[p_{d1m}, \ldots, p_{d7m}]$ for Model 2.

Using the self-stated screening bin membership data, map $[p_{d1m}, \ldots, p_{d8m}]$ to $[p_{d1m}^*, \ldots, p_{d8m}^*]$ so that $p_{d1m}^* = p_{dbm}$ and $p_{dbm}^* = p_{d1m}$ if $\omega_{dm}^* = w^b$. Then,

$$\begin{aligned} & f([p_{1m}, \ldots, p_{7m}] \mid \{\omega_{dm}\}) \\ &\quad \propto \prod_{d=1}^{n} f(\omega_{dm} \mid [p_{1m}, \ldots, p_{7m}]) \times f([p_{1m}, \ldots, p_{7m}]) \\ &\quad \sim \text{generalized Dirichlet}(\alpha^*, \zeta^*), \end{aligned}$$

such that $\alpha_{bm}^* / (\alpha_{bm}^* + \zeta_{bm}^*) = \mu_b$ for $b = 1, 2, \ldots, 7$, and $p_{d8m}^* = 1 - p_{d1m}^* - \cdots - p_{d7m}^*$. We choose the values for α_{bm}^* [40, 7.14, 8.33, 10, 12.5, 16.67, 25] and ζ_{bm}^* [10, 42.86, 41.67, 40, 37.5, 33.33, 25] so that $\mu_1 = 80\%$, $\alpha + \zeta = 50$, and the expected standard deviation of p_{dbm}^* is equivalent across b (see p. 174 of Wong 1998 for more details).

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