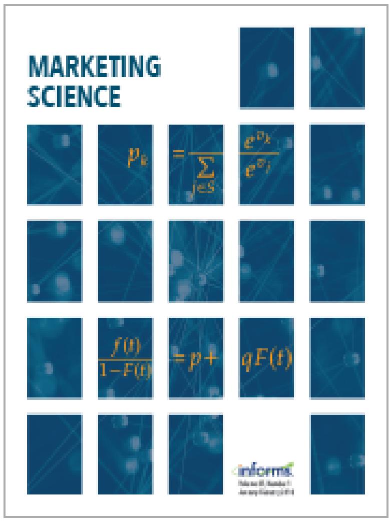

Marketing Science

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

MARKETING SCIENCE
Vol. 36, No. 3, May–June 2017, pp. 436–452
ISSN 0732-2399 (print), ISSN 1526-548X (online)

Dyadic Compromise Effect

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Received: December 13, 2013
Revised: July 30, 2015; March 25, 2016; August 5, 2016
Accepted: August 19, 2016
Published Online in Articles in Advance: March 17, 2017

https://doi.org/10.1287/mksc.2016.1019

Abstract. Existing research on the compromise effect has focused exclusively on the individual. This paper investigates compromise effects in a setting that involves multiple individuals making a choice. We study whether the dyadic compromise effect (DCE) exists, the association between dyadic and individual compromise effects, and strategies to mitigate the DCE. We build a statistical model of dyadic choice that formally incorporates DCE. We conduct two studies to test our proposed models empirically. In Study 1, we begin with an investigation of the DCE with student subjects. In Study 2, we test for the presence of DCE among married couples when making retirement investment choices. In both studies, model-free and model-based evidence provides strong support for the presence of DCE. A model that incorporates DCE provides a better fit than models that do not. Evidence in support of DCE is shown to be robust to alternative compromise effect model specifications and utility aggregation methods. We find that the individual compromise effect tendency of a group member with a greater stake in the decision is likely to persist as a DCE in the joint choice setting. Our findings suggest that education of segments vulnerable to compromise effects reduces the DCE.

History: Preyas Desai served as the editor-in-chief and Scott Neslin served as associate editor for this article.
Supplemental Material: Data and the web appendix are available at https://doi.org/10.1287/mksc.2016.1019.

Keywords: group decisions • compromise effects • group choice • family decisions • financial planning • behavioral economics

1. Introduction

The compromise effect has been studied extensively in marketing—its basic prediction is that an alternative will gain shares when it becomes the intermediate option in a choice set. For example, when selecting a cell phone package or an Internet plan, an individual may feel more comfortable selecting the middle option instead of an extreme one. This occurs because the selection of the intermediate option is easier to justify, is less likely to be criticized (Simonson 1989), and is consistent with loss aversion (Simonson and Tversky 1992). Since Simonson's (1989) seminal paper first illustrated this effect, marketing scholars have investigated antecedents and moderators of the compromise effect (e.g., Dhar et al. 2000, Nowlis and Simonson 2000, Drolet 2002, Chernev 2004) and incorporated this effect into formal choice models (Kivetz et al. 2004a, Sharpe et al. 2008, Rooderkerk et al. 2011).

Existing research on the compromise effect has focused exclusively on the individual. Another context in which the compromise effect may be highly relevant is when a group of individuals makes a joint decision. Examples include family purchases (e.g., an appliance) and organizational buying (e.g., hospital equipment). In the simplest of scenarios, consider a husband–wife dyad selecting a washer and dryer at a Sears store. In this example it is reasonable to ask whether the tendency to select the intermediate option, namely, the one with average quality and average price, is magnified in the dyadic choice context. Theoretically, there are several reasons for the existence of compromise effects at the dyadic level: an uncertain decision environment, a greater need to justify the decision, and a greater likelihood of attributes becoming equally important. As we explain in Section 2.1, the existing literature suggests that these reasons explain why the dyadic choice area is a fertile ground for the presence of compromise effects.

The primary purpose of this paper is to investigate compromise effects in a dyadic setting. We first define the term *dyadic compromise effect* (*DCE*) as a dyad's tendency to choose an intermediate option after accounting for the compromise effect and influence of each individual member within the dyad. We study whether dyads, like individuals, exhibit the compromise effect. We also explore the association between dyadic and individual level compromise effects. Finally, we study whether the dyadic compromise effect can be mitigated so that the choice a dyad makes is not unduly affected by the presented options or the choice context.

The dyadic choice setting presents several conceptual and methodological challenges to investigate compromise effects. First, within a dyad, the preference of each individual involved in the purchase decision needs to be measured. Second, each individual's influence needs to be assessed in addition to their preference. Third, the individual compromise effect (ICE) needs to be separated from the dyadic compromise effect. We rely on two streams of literature to overcome these challenges: statistical models of group choice and individual level compromise effects.

We model DCE after controlling for ICE, an important step to be able to demonstrate the existence of DCE regardless of the existence of ICE. Furthermore, a dyad could select the middle option because it maximizes the influence-weighted individual utilities or because of the dyadic compromise effect. In our model specification, we allow for each possibility. Both DCE and influence-weighted utility aggregation are accounted for in the dyadic choice process. The model allows us to uncover DCE after explicitly accounting for influence-weighted utility aggregation. We model DCE as a context effect and note that it is conceptually distinct from member influence and utility aggregation.

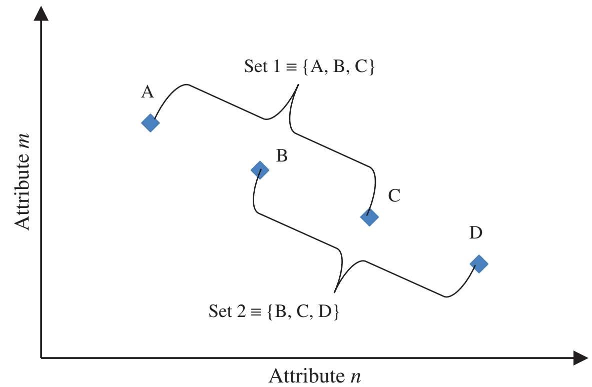
In our models, the ICE is captured by transforming context-independent utility into a more concave context-dependent utility, as suggested by Kivetz et al. (2004a) and Sharpe et al. (2008) (hereafter, KNS and SSH, respectively). The basic premise is that the utilities of attribute levels are measured at a global, *context-independent* level with methods such as a ratings-based conjoint analysis. The global utility function can be linear, concave, or convex. The models then transform the global, context-independent utilities into *context-dependent* utilities according to the local context or based on options in a choice set. In other words, context-dependent preference is measured in a local choice context. By contrast, context-independent preference is measured at a global level and does not involve a choice decision. To capture the DCE, we add another layer of concavity to the dyad's preference in a model that also incorporates individual preferences as well as their influence (Arora and Allenby 1999). Our full model of dyadic choice incorporates individual preference and influence and accounts for individual and dyadic compromise effects. This full model also allows us to test simpler nested models for comparison.

We conducted two studies to test our proposed model. In Study 1, we began with an investigation of DCE with student subjects. In Study 2, we tested for the presence of DCE in a setting in which married couples are asked to make retirement investment choices. We reported model-free evidence in support of DCE for both studies. Referring back to the definition of DCE, the only conclusive way to test for DCE was by using a model that controls for ICE and influence. We found that a model that incorporates DCE provides a better fit than a model that does not. Evidence in support of DCE is robust to alternative compromise effect model specifications (KNS, SSH) and utility aggregation methods (Harsanyi 1955, Nash 1953). Our model provides evidence for DCE after properly accounting for ICE and member influence and presents the statistical machinery to predict dyadic choice better.

We found that greater ICE is associated with greater DCE. Furthermore, the ICE tendency of a group member with a greater stake in the decision appears to have a stronger association with DCE. Because compromise effects allow a seller to manipulate buyer choice by simply altering the choice set composition, we investigated means to mitigate them. Our findings suggest that choice sets with fewer options help reduce DCE. Moreover, the education of market segments most vulnerable to compromise effects (e.g., women in the context of retirement planning as in Study 2) may be an effective method to mitigate DCE.

The remainder of this paper is organized as follows. In Section 2, we review related literature and describe our conceptual framework. In Section 3, we then lay out our modeling framework. In Section 4, we present two studies and key empirical findings. We close with a discussion of our main findings in Section 5.

Figure 1. (Color online) Illustration of the Compromise Effect



2. Conceptual Background

2.1. Literature Review

We begin with an overview of past work on the individual-level compromise effect followed by a conceptual development of dyadic compromise effects.

Following Simonson (1989), we illustrate the compromise effect in Figure 1. Consider alternatives A, B, C, and D, which vary on two dimensions: attributes m and n. The main finding pertaining to the compromise effect is that the share of option B relative to that of option C is greater in the set {A, B, C} than in the set {B, C, D}. Option B is the middle option in {A, B, C} and an extreme option in {B, C, D}.

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The compromise effect has been largely explained as a context effect in terms of constructive preferences (e.g., Bettman et al. 1998); that is, preference is endogenous to the local choice set. The selection of a compromise option is a result of taking into account local, relative characteristics of the alternatives in the choice set when consumers are uncertain about their global assessment of the alternatives. Simonson (1989) argues that the selection of the intermediate option is easier to justify than an extreme option and less likely to be criticized. A compromise choice can reduce the conflict associated with giving up one attribute for another (Sheng et al. 2005) when, for example, selecting a low-price option and foregoing the high-quality option. Simonson and Tversky (1992) explain the compromise effect using the loss aversion theory. They argue that the disadvantages of an extreme option loom larger than the advantages, leading to the compromise effect.

The dyadic compromise effect, as noted previously, refers to a dyad's tendency to select an intermediate option in a joint choice decision. Theoretically, there are two compelling reasons for the existence of DCE: an uncertain decision environment and greater likelihood of symmetric attributes. First, dyadic settings are unique because they are characterized by a great deal of uncertainty about other members' preferences. For example, Arora (2006) provides empirical evidence that members within a group have limited knowledge about others in the group. Greater decision uncertainty causes an increase in individual-level compromise effects (Sheng et al. 2005). Therefore, it is likely that choices in dyadic settings exhibit DCE. In their paper, Dhar et al. (2004) make a similar argument that compromise effects may be amplified in complex buying situations involving groups of individuals because consensus may be hard to reach, thereby increasing uncertainty about other individuals' preferences.

Second, preference aggregation is likely to enhance the likelihood that attribute importance becomes more symmetric for the dyad. For example, in a two-attribute (A1, A2) example, if A1 is more important to one member and A2 to another, then for the dyad the two attributes likely become equally important. In other words, the attribute importance becomes more symmetric at the dyadic level. Approximately equal relative importance for a pair of attributes creates an environment well suited for compromise effects; the converse results in the polarization effect (Tversky and Simonson 1993). Making similar arguments, Kivetz et al. (2004b, p. 264) observe that "the issue of whether groups are more likely than individuals to select compromise (and asymmetrically dominating) options merits further research" and that "utility functions derived by such an approach as that of Arora and Allenby (1999), combined with KNS (2004a) models, can indeed capture multiperson compromise effects." Such arguments are well aligned with the central focus of this research.

As we alluded to earlier, conceptually and methodologically, several aspects of the joint choice setting make it difficult to demonstrate the presence of dyadic compromise effects. In the following illustration, we highlight these aspects, as well as the specific role the dyadic compromise effect may play in a joint choice decision.

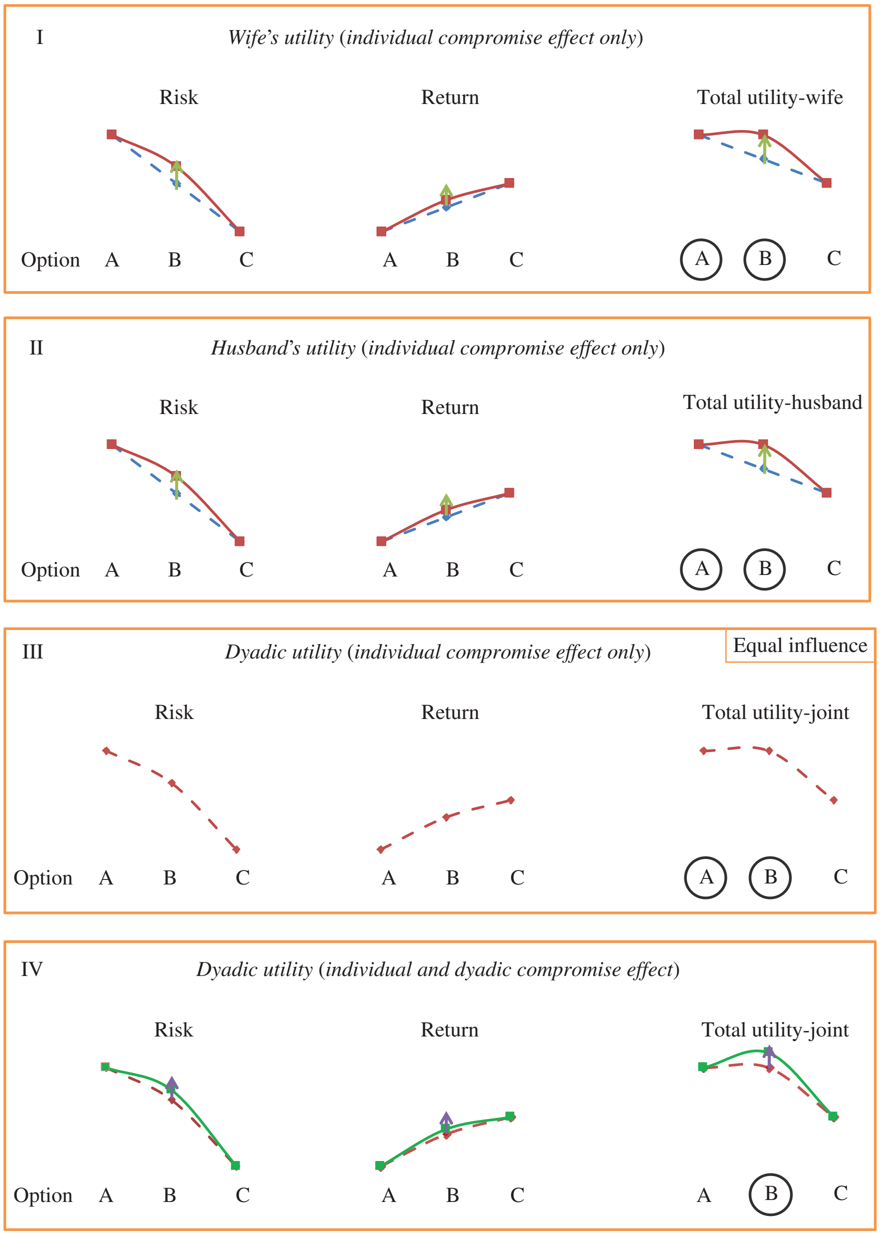
2.2. Illustration of the Dyadic Compromise Effect

In this hypothetical example, a husband and wife choose among three financial investment portfolios varying on risk and return. The example is consistent with the normalized contextual concavity model in Kivetz et al. (2004a). In Figure 2, fund A offers the lowest expected return and the lowest risk, fund C is the opposite (highest return, highest risk), and fund B is in the middle (medium return, medium risk). Panel I of Figure 2 shows the context-independent utility function for the wife in this example (shown by the dashed line). As suggested by Kivetz et al. (2004a), the context-independent utility is based on an evaluation of one alternative at a time, whereas the context-dependent utility corresponds to a situation that involves multiple choice alternatives. For the risk attribute, the utility function is downward sloping (more is worse), while for the return (more is better) it is upward sloping. The wife's total context-independent utility for options A, B, and C, also shown by the dotted line, indicates that A should be her preferred option as it has the highest utility.

When evaluating all three options (A, B, C) in a choice set, the wife in our example is prone to the compromise effect; as a result, her context-independent utility function for each attribute (the dashed line) is transformed into a more concave context-dependent utility function (the solid line). Because of the compromise effect, the intermediate option B gains utility and becomes as attractive as option A; consequently, the wife is likely to choose the circled options A *or* B. For the husband in our example, the context-independent and context-dependent utility functions are shown in panel II of Figure 2. Like his wife, the husband also prefers a low-risk investment with low return and, because of the individual compromise effect, is likely to choose the circled options A or B (they have equal utility for him as well).

Panel III combines individual utilities to demonstrate what the dyad may choose collectively. The utilities in Panel III are the average of those in panels I and II because of equal influence. We combine context-dependent individual preferences assuming that each individual has equal influence in the joint choice. The result indicates that options A and B have the highest dyadic utility after the individual preferences are combined, so the dyad may be indifferent when choosing between options A and B. Panel IV illustrates how the

Figure 2. (Color online) Graphical Illustration of the Dyadic Compromise Effect



Notes. In panels I and II, the dashed lines refer to the individual-level context-independent utilities, and the solid lines denote context-dependent utilities incorporating the ICE. In panels III and IV, the dashed lines are the dyadic utilities after incorporating only the ICE, while the solid lines denote the dyadic utilities incorporating both the ICE and DCE. In each panel, the circled options have the highest utility.

dyadic compromise effect may play a role. The dyad's utility of the middle option is higher, as seen by the solid line to capture the dyadic compromise effect. This could occur because the dyad is collectively more likely to avoid selecting the extreme, much too conservative option A (lowest risk, lowest return). After the dyadic compromise effect is incorporated into the utility function, option B enjoys a higher utility than option A (and C) and is therefore selected.

The above illustration demonstrates how the dyadic compromise effect may manifest itself in joint choice decisions. Next we describe a statistical model that captures different nuances of the dyadic choice process.

3. Dyadic Compromise Effect Model

We rely on two streams of literature to build our statistical model: group choice and the individual-level compromise effects. This model could be viewed as a paramorphic representation of dyadic choice that allows us to (i) test for the presence of DCE and (ii) improve our ability to predict those choices. We rely on Arora and Allenby (1999) to model dyadic choice and KNS and SSH to model the compromise effect. Following the KNS and SSH models, we conceptualize our compromise effect model at the attribute level. The model assumes that the decision makers make choices *as if* they are consistent with the compromise effects that occur at the level of the attribute and makes no claim about uncovering process-level details.

We divide the model development part into the following sections: context-independent preference, context-dependent preference, and utility aggregation and the dyadic compromise effect.

3.1. Context-Independent Preference (Individual)

Let subscripts i, j, m, and k refer to consumer i, product alternative j, attribute m, and attribute level k, respectively. The individual context-independent utility can be written as

$$u_{ij} = \sum_m \sum_k u_{ijmk} + \varepsilon_{\mathrm{ij}} = \sum_m \sum_k x_{ijmk}\beta_{\mathrm{imk}} + \varepsilon_{\mathrm{ij}}, \tag{1}$$

where x_{ijmk} corresponds to level k for attribute m in each alternative j that person i evaluates. The error term $\varepsilon_{ij} \sim \mathrm{Normal}\,(0, \sigma_i^2)$ and β_{imk} is the context-independent preference measured at the global level using a method such as ratings-based conjoint.

3.2. Context-Dependent Preference (Individual)

In Equation (1), context-independent preference β_{imk} is allowed to take any shape. Similar to KNS, we assume that when consumer i is confronted with a choice set, their preference may change because of the local context—that is, the choice options they see. In the presence of such choice data, the context-independent preference β_{imk} is transformed into a more concave function through a concavity parameter c_{im}, which captures the individual compromise effect when $0 < c_{im} < 1$. The more concave the utility function is (the closer c_{im} is to 0), the stronger the individual compromise effect. Following KNS, the context-dependent preference of level k in attribute m is written as[1]

$$\begin{aligned}\beta^S_{imk} &= (\beta^S_{i,m,\max} - \beta^S_{i,m,\min}) \\ &\quad \times [(\beta_{imk} - \beta^S_{i,m,\min})/(\beta^S_{i,m,\max} - \beta^S_{i,m,\min})]^{c_{im}},\end{aligned} \tag{2}$$

where the parameters are as follows:

- β^S_{imk} is the individual's context-dependent preference of level k for attribute m in choice set S;
- β_{imk} is the individual's context-independent preference of level k for attribute m;
- $\beta^S_{i,m,\min}$ is the individual's lowest preference on attribute m in choice set S;
- $\beta^S_{i,m,\max}$ is the individual's highest preference on attribute m in choice set S;
- c_{im} is the concavity parameter of attribute m for individual i. For the purpose of estimation, c_{im} is reparameterized as $\exp(\eta_{im})$ so that $c_{im} > 0$.

Referring back to Figure 2 (top two panels), the concavity parameter c_{im} can change the comparative values of the utility for intermediate levels. Different values of c_{im} can transform the context-independent utility of the intermediate levels into bigger ($0 < c_{im} < 1$), smaller ($c_{im} > 1$), or same-valued ($c_{im} = 1$) context-dependent utility. In the illustrative example for Figure 2, in panels I and II, we used $c_{im} = 0.57$ to make this aspect of the model more concrete.

Unlike the KNS specification, Sharpe et al. (2008) proposed a model to capture the individual compromise effects. Our model development from this point will focus on the SSH model,[2] in which the context-independent preference β_{imk} is obtained as in Equation (1). By contrast to the KNS model that imposes a concave utility function across all levels of an attribute to capture the compromise effect, the SSH model allows only the two extreme options to have a different context-dependent utility from the context-independent utility

$$\begin{aligned}\beta^S_{imk} = \beta_{imk} &- \gamma_{im} I(k \text{ is the lowest level of attribute } m \text{ in choice set } S), \\ &- \phi_{im} I(k \text{ is the highest level of attribute } m \text{ in choice set } S).\end{aligned} \tag{3}$$

In the presence of ICE, γ_{im} and ϕ_{im} are expected to be positive. This would be consistent with the extremeness aversion hypothesis. Conversely, negative γ_{im} and ϕ_{im} suggest extreme seeking behavior. For parsimony, we simplify the SSH model by constraining the extreme aversion terms for the highest and lowest levels to be the same

$$\beta^S_{imk} = \beta_{imk} - \gamma_{im} I(k \text{ is an extreme level of attribute } m \text{ in choice set } S). \tag{4}$$

Equation (4) implies that *all* of the intermediate options in a choice set have a utility gain compared to the context-independent utility. A stricter variant of the SSH model could be specified in which *only* the middle option has a utility gain compared to the context-independent utility

$$\beta^S_{imk} = \beta_{imk} + \mu_{im} I(k \text{ is the middle level of attribute } m \text{ in choice set } S). \tag{5}$$

In the presence of the middle option experiencing utility gain, μ_{im} is expected to be positive. Unlike the SSH model in Equation (4) that models ICE by extreme attenuation (EA), Equation (5) focuses on middle amplification (MA). The distinction between EA and MA is not relevant when there are only three alternatives in a choice set. The middle option is the only intermediate option. However, for a greater number of options (e.g., five), the difference between the two specifications is meaningful. Such larger choice sets point to an undesirable feature of Equation (5)—the MA model assumes that the context dependent utility of the intermediate options that are *not* in the middle remain unchanged. The MA model is therefore not strictly consistent with the definition of the compromise effect, which very clearly states that an alternative will gain shares when it becomes the intermediate option. Given that the EA model has been applied in the past (SSH) and that it is more consistent with the definition of the compromise effect, we will continue our model development using the SSH model.[3]

Alternative j's context dependent utility can then be written as

$$u_{ij}^{\mathrm{S}} = \sum_{m}\sum_{k} x_{ijmk}\beta_{imk}^{S} + \varepsilon_{\mathrm{ij}}. \tag{6}$$

The error term is assumed to follow the extreme value $(0,1)$ distribution. The probability that consumer i chooses alternative j in the context S follows the multinomial logit model:

$$\Pr(y_{iS} = j) = \frac{\exp(b_i \sum_m \sum_k x_{ijmk}\beta_{imk}^{S})}{\sum_{j=1}^{J}\exp(b_i \sum_m \sum_k x_{ijmk}\beta_{imk}^{S})}. \tag{7}$$

The scale parameter b_i is present because two data sources are involved in the separate assessment of context-independent and context-dependent preferences (Hensher et al. 1999).

3.3. Utility Aggregation and the Dyadic Compromise Effect

Analogous to the individual-level setup above, we next model the dyadic context-independent preference (β_{gmk}) and context-dependent preference (β_{gmk}^{S}). Similar to the case of the individual, β_{gmk} is the dyadic context-independent preference measured at the global level using a method such as the ratings-based conjoint. The link between individual and dyadic preference is established using a weighted utility aggregation model (Harsanyi 1955) that is widely used in marketing (e.g., Gupta and Kohli 1990, Arora and Allenby 1999, Aribarg et al. 2002). This utility aggregation model has been shown to outperform multiplicative Nash models, Rawls model, and models that minimize regret (e.g., Aribarg et al. 2010, Yang et al. 2010). The weighted utility aggregation model can help assess the influence of each individual in a joint decision at the level of an attribute (θ_{gm}). Formally, let i_1 and i_2 denote individuals in dyad g. The dyadic preference β_{gmk} is given by

$$\beta_{gmk} = \theta_{gm}\beta_{g,i_1mk} + (1-\theta_{gm})\beta_{g,i_2mk}; \tag{8}$$

that is, the dyadic preference is a weighted sum of context-independent preferences of individuals. Equation (8) is used to identify θ_{gm}, namely, the attribute-specific influence parameter. When dyads make choices, the individual compromise effect may still be present. We incorporate the individual compromise effect in the dyadic choice process by creating the term $\tilde{\beta}_{gmk}$, where

$$\tilde{\beta}_{gmk} = \theta_{gm}\beta_{g,i_1mk}^{S} + (1-\theta_{gm})\beta_{g,i_2mk}^{S}. \tag{9}$$

The term $\tilde{\beta}_{gmk}$ incorporates the individual compromise effects when a dyad is making a joint choice decision. In Equation (9), we simply combine the β_{g,i_1mk}^{S} and β_{g,i_2mk}^{S} parameters (Equation (4)) using the influence parameter (Equation (8)). Finally, when a dyad is confronted with a choice set, its preference may change because of the dyadic compromise effect—that is, the intermediate options may gain additional utility in the dyadic setting because of the local context. Similar in spirit to Equation (4),

$$\beta_{gmk}^{S} = \tilde{\beta}_{gmk} - \tau_{gm}I(k \text{ is an extreme level of attribute } m \text{ in choice set } S). \tag{10}$$

The parameter τ_{gm} is expected to be positive when DCE is present. Please refer to the web appendix for a KNS equivalent of Equation (10).

Last, analogous to the setup at the individual level, the group's context-dependent utility given by $u_{gj}^{\mathrm{S}} = \sum_m \sum_k x_{gjmk}\beta_{gmk}^{S} + \varepsilon_{\mathrm{gj}}$ and the probability that dyad g chooses alternative j in the context S follows a multinomial logit model with a scale parameter d_g:

$$\Pr(y_{gS} = j) = \frac{\exp(d_g \sum_m \sum_k x_{gjmk}\beta_{gmk}^{S})}{\sum_{j=1}^{J}\exp(d_g \sum_m \sum_k x_{gjmk}\beta_{gmk}^{S})}. \tag{11}$$

As before, the scale parameter d_g is present because two different data sources are involved in the separate assessment of context-independent and context-dependent dyadic preferences.

As we noted earlier, two aspects of the model should be mentioned. First, DCE is modeled (Equation (10)) after controlling for ICE (Equation (4)). This is important because we are interested in uncovering the DCE over and above the ICE. The proposed model is flexible because it allows for the presence, or absence, of ICE for either member in the dyad. Furthermore, it allows for the presence or absence of DCE after having accounted for ICE. Second, DCE is modeled (Equation (10)) separately from the member influence parameter (Equation (8)). Conceptually, it is important to do so: A dyad could arguably select the middle option because it maximizes the influence-weighted individual utilities or because of the dyadic compromise effect. In our model specification, we allow for each possibility: both DCE (τ_{gm}) and influence (θ_{gm})-weighted utility aggregation are accounted for in the dyadic choice process. The model allows us to uncover DCE after explicitly accounting for the influence-weighted utility aggregation.

Thus far, the model development has focused on a given dyad. For each dyad, the vector of model parameters includes individual-level preference, compromise effect, and scaling parameters (β, γ, b) for each member, and dyad-level relative influence, compromise effect, and scaling parameters (θ, τ, d). These individual and dyadic parameter estimates are expected to be heterogeneous. In our model, we assume that the heterogeneity distributions for these parameters are multivariate normal. These details, along with complete model estimation algorithms, are included in the web appendix.

Next we test our proposed models empirically. We begin with a study that helps uncover the individual- and dyadic-level compromise effects in a lab setting. This is followed by a study to assess the dyadic compromise effect and its association with the individual compromise effect in the context of a financial decision by using husband–wife dyads.

4. Empirical Application

4.1. Study 1

The steps involved in the data collection for Study 1 are reported in Table 1. Following KNS, part 1 is intended to assess the context-independent preference of each individual using a ratings-based conjoint exercise. In part 2, individuals are asked to make choices from a series of Pareto-optimal choice sets to uncover the context-dependent preference. Collectively, parts 1 and 2 allow us to test for the presence of compromise effect at the individual level. In part 3, we ask the dyads to complete a ratings-based conjoint task together—thus, parts 1 and 3 allow us to assess the influence parameters (Arora and Allenby 1999). Finally, in part 4, the dyads are asked to make choices from a series of Pareto-optimal choice sets to uncover dyadic context-dependent preference. Collectively, parts 1 through 4 allow us to test for the presence of DCE after accounting for member influence and individual-level compromise effect.

4.1.1. Participants and Procedure. A total of 522 undergraduate students in a midwestern university participated in this study in exchange for extra credit. We assigned the respondents to two groups—individual and dyadic task group (Study 1A; $n = 312$) and dyadic-only task group (Study 1B; $n = 210$). The respondents were given the hypothetical task of buying an all-in-one printer for a student organization for which they were a copresident. Following the study flow shown in Table 1, in part 1, each individual respondent was asked to rate 14 conjoint profiles on a 1–100 scale. In part 2, each respondent chose all-in-one printers from 12 Pareto-optimal choice sets. In part 3, 2 respondents were randomly matched to complete the same 14 rating conjoint tasks together as a group. In part 4, each group chose all-in-one printers from the same 12 Pareto-optimal choice sets as in part 2. Consistent with the studies conducted by KNS and SSH, part 2 preceded part 1, while part 4 preceded part 3. We followed this order to ensure that the choices from Pareto-optimal sets were not biased by the ratings-based conjoint task. Respondents assigned to Study 1A finished parts 1 through 4 of the study (number of dyads = 156); those assigned to Study 1B finished parts 3 and 4 only (number of dyads = 105).

Our study design focused on three attributes: price, speed, and resolution. The attribute levels were based on the typical values found in the market at the time of data collection (price = \$119 to \$719, in increments of \$100; speed = 10 to 40 pages per minute, in increments of 5 pages per minute; resolution = 300×300 to 1200×1200 dots per inch). In the ratings-based conjoint task (14 profiles; 1–100 scale), the product profiles contained all 3 attributes. All of the attribute levels in Pareto-optimal choice sets in parts 2 and 4 are included in the conjoint tasks. Figure A in the web appendix shows an example of the ratings-based conjoint exercise.

For parts 2 and 4 of the study, each Pareto-optimal choice set has six options: five options involving different levels of product attributes and a "no-choice" option. The five options are described either on all three attributes (see Figure B in the web appendix) or on two attributes. The three-attribute Pareto-optimal choice set design is similar to the design in KNS and SSH.

The inclusion of all attributes in one choice set restricts the number of Pareto-optimal choice sets that can possibly be generated, thereby limiting the amount of choice data. To remove this restriction, we created a choice design that involves two attributes at a time. For such two-attribute choice sets, three attribute combination pairs exist: {(price, speed); (price, resolution); (speed, resolution)}. For each combination (e.g., speed and resolution), three choice sets were created. This resulted in nine (three choice sets per combination × *three* combinations) two-attribute Pareto-optimal choice sets per respondent. In the survey, the three three-attribute Pareto-optimal choice sets were followed by the nine two-attribute Pareto-optimal choice sets. Filler questions were included between these Pareto-optimal choice sets. One of the three-attribute Pareto-optimal choice sets was used as a holdout in the predictive analyses. Our study design included repeated choices and is similar in spirit to Sharpe et al. (2008) and Rooderkerk et al. (2011). This is in contrast with most of the original demonstrations of the compromise effect (e.g., Simonson 1989), which involved only one choice set per respondent.

4.1.2. Model-Free Results. We first look at model-free evidence for the dyads' tendency to choose interme-

Table 1. Study 1 Flow

Part	Data source	Task	Objective	Task details	Study 1A	Study 1B
1	Individual	Ratings-based conjoint	To obtain each member's context-independent preference	• Three attributes: price, speed, resolution; each attribute had seven levels. • Fourteen profiles/ respondent	$N = 312$ individuals	No individual data
2	Individual	Choice	To obtain each member's context-dependent preference and individual compromise effect	• Choice tasks were constructed using two separate design approaches ∘ Three attributes: Each choice alternative described on all three attributes (total of three such choice tasks; randomized) ∘ Two attributes: Each choice alternative described on two attributes (total of nine such choice tasks; randomized) • Choice set: five alternatives plus a no-choice option • In total, 12 choice tasks/person		
3	Dyad	Ratings-based conjoint	To obtain each dyad's context-independent preference and influence	• Three attributes: price, speed, resolution; Each attribute had seven levels • Fourteen profiles/ respondent	$N = 156$ dyads	$N = 105$ dyads
4	Dyad	Choice	To obtain each dyad's context-dependent preference and dyadic compromise effect	• Choice tasks were constructed using two separate design approaches ∘ Three attributes: Each choice alternative described on all three attributes (total of three such choice tasks; randomized) ∘ Two attributes: Each choice alternative described on two attributes (total of nine such choice tasks; randomized) • Choice set: five alternatives plus a no-choice option • In total, 12 choice tasks/person		

diate options in Study 1A. The compromise effect can be statistically tested by comparing the shares of an option when it is an extreme option versus the share of this option when it is an intermediate option (Simonson and Tversky 1992). Table 2 shows the market shares of choice options in three different scenarios (sets 1, 2, and 3). We focused on options E and C because they are the extreme options in one choice set, and intermediate options in other choice sets. E's market share was 15.4% when it was an extreme option in set 1, but its shares were 16.7% and 30.1% in sets 2 and 3, respectively, when it was an intermediate option. This creates a difference of 8% ((30.1% + 16.7%)/2 − 15.4%), thereby providing model-free evidence in support of DCE. A similar pattern emerged when we compared the market share of model C across the three sets (22.4%, 26.9%, and 44.2%; difference = 13.2%). The compromise effect measures were statistically significant ($p < 0.05$) for both C and E. Similar tests for compromise effects in Study 1B revealed an identical pattern: the difference

Table 2. Choice Options and Dyadic Shares in the Printer Category (Study 1A)

				Dyadic shares		
Model	Speed (ppm)	Resolution (dpi)	Price ($)	Set 1 (%)	Set 2 (%)	Set 3 (%)
A	10	300 × 300	119	11.5		
B	15	600 × 300	219	10.3	13.5	
C	20	600 × 600	319	44.2	26.9	22.4
D	25	900 × 600	419	17.3	33.3	28.8
E	30	900 × 900	519	15.4	16.7	30.1
F	35	1200 × 900	619		9.0	8.3
G	40	1200 × 1200	719			7.7
No choice				1.3	0.6	2.6

Note. ppm, pages per minute; dpi, dots per inch.

measure was significant for both C (11.9%; $p < 0.05$) and E (12.0%; $p < 0.05$). This result indicates that dyadic tasks in Study 1A were not biased by the preceding individual tasks.

Model-free evidence in support of compromise effects in dyadic choices is encouraging, but not entirely conclusive. As we stated previously, the statistical model we propose is designed to test for the presence of DCE after accounting for ICE and influence-weighted utility aggregation. Such a model also allows us to predict dyadic choices. In Section 4.1.3, we test for the presence of DCE in a statistical model and whether the inclusion of DCE in a model of dyadic choice results in predictive gains.

4.1.3. Model Fit. First, we compared models without ICE and DCE with those that include compromise effects. We also compared the full (i.e., ICE and DCE) compromise effect model for the two alternative specifications: SSH and KNS. Second, we compared results from the three-attribute choice design with the two-attribute design. Third, we compared the results from full data (parts 1 through 4) with dyadic data (parts 3 and 4) to assess the incremental value of obtaining individual data over dyadic data alone. Finally, in addition to the linear utility aggregation (Equation (8)), we also tested the asymmetric Nash utility aggregation model (Nash 1950, Roth 1979), which has been shown to predict cooperative negotiation or nonzero-sum game outcomes quite well (Curry et al. 1991, Eliashberg et al. 1986, Neslin and Greenhalgh 1983).[4]

The Nash model for cooperative games aggregates utilities simply by multiplying utilities of members in a group (Davis 1970; Luce and Raiffa 1957; Nash 1950, 1953; Owen 1969). Roth (1979) extended the original Nash model to allow asymmetric influences across members by incorporating different decision weights for each member (Binmore et al. 1986, Peters and Van Damme 1991). The dyad's utility associated with an alternative derived from the weighted Nash model can be written as $u_d = (u_1 - u_{10})^{w_1} \cdot (u_2 - u_{20})^{w_2}$, where u_1 and u_2 are utilities associated with members 1 and 2, respectively. Furthermore, u_{10} and u_{20} are utilities corresponding to the "no-settlement" situation for each member. The weights w_1 and w_2 reflect member influence.

We adapted the Nash model to the context of this paper in the following manner (also see Aribarg et al. 2010, p. 154). To estimate the influence parameters using ratings data, we changed Equation (8) to reflect Nash's multiplicative utility aggregation, that is, $\beta_{gmk} = \beta^{\theta_{gm}}_{g,i_1mk}\beta^{(1-\theta_{gm})}_{g,i_2mk}$. We viewed the "no-choice" option as the "no-settlement" option and rewrote Equation (9) as

$$\tilde{\beta}_{gmk} = (\beta^S_{g,i_1mk} - \beta^S_{g,i_{10}mk})^{\theta_{gm}}(\beta^S_{g,i_2mk} - \beta^S_{g,i_{20}mk})^{(1-\theta_{gm})}.$$

Here $\beta^S_{g,i_{10}mk}$ and $\beta^S_{g,i_{20}mk}$ are preferences for the "no-choice" option, commonly modeled (see, for example, Gilbride and Allenby 2004) by setting the "no-choice" utility to zero. Following the same logic, we set both $\beta^S_{g,i_{10}mk}$ and $\beta^S_{g,i_{20}mk}$ to zero when estimating the Nash version of our proposed model.

The in-sample model fit statistics include log marginal density (LMD) and deviance information criterion (DIC) (Newton and Raftery 1994, Spiegelhalter et al. 2002). LMD is a likelihood-based measure calculated using the harmonic mean across iterations; DIC incorporates a number of parameters in its calculation, thereby penalizing models that tend to overfit the data. Mean absolute error (MAE)[5] and hit rate measure out-of-sample fit and are routinely used to assess prediction quality in choice models. The validation task is a six-alternative Pareto-optimal choice set that varies on all three attributes and includes the no-choice option.

The model comparison results are displayed in Table 3. Focusing on the three-attribute SSH model, we found that incorporating individual-level compromise effects results in better in-sample and out-of-sample fit (Model 1 versus Model 2). Incorporating the dyadic compromise effect resulted in further gains in both types of fit (Model 2 versus Model 3). This pattern of results provided evidence supporting the presence of compromise effects at the individual and dyadic levels. Furthermore, compared with KNS, the SSH-based

Table 3. Study 1A Model Comparison

	Model description						In-sample fit		Out-of-sample fit	
No.	No. of attributes (choice design)	Compromise effect model	ICE	DCE	Utility aggregation	Data from parts	LMD	DIC	Hit rate[a] (%)	MAE
1	3	No	No	No	Linear	1–4	−1,522	7,684	19.8	0.086
2	3	SSH	Yes	No	Linear	1–4	−1,398	7,059	27.6	0.073
3	3	SSH	Yes	Yes	Linear	1–4	−1,234	6,234	33.8	0.067
4	3	KNS	Yes	Yes	Linear	1–4	−1,428	7,353	23.0	0.068
5	3	SSH	Yes	No	Nash	1–4	−2,196	7,719	27.0	0.097
6	3	SSH	Yes	Yes	Nash	1–4	−2,185	7,688	29.0	0.085
7	2	No	No	No	Linear	1–4	−6,886	33,045	19.8	0.089
8	2	SSH	Yes	No	Linear	1–4	−6,738	30,233	30.5	0.067
9	2	SSH	Yes	Yes	Linear	1–4	−6,115	28,677	33.8	0.066
10	3	SSH	No	Yes	Linear	3, 4	−501	1,930	27.8	0.067
11	3	SSH	No	Yes	Linear	1, 3, 4	−1,398	7,056	27.8	0.067

[a]The hit rate is based on a validation task of six alternatives. The choice outcome for a Pareto-optimal task, by design, is difficult to predict. The hit rates are comparable in magnitude to what has been reported by others (e.g., Gilbride and Allenby 2004) in large-set-size contexts.

model performed better (Model 3 versus Model 4) on the in-sample[6] and out-of-sample fit criteria. The Nash utility aggregation models (Models 5 and 6) did not perform as well as their linear counterparts (Models 2 and 3). Therefore, in the remainder of this paper, we report results based on the SSH-based model. Results for the KNS-based model and the Nash model followed a very similar pattern for ICE and DCE parameters and are reported in Tables A and B in the web appendix.

The two-attribute SSH-based models followed a similar pattern as the three-attribute SSH-based models reported earlier. The model incorporating ICE and DCE (Model 9) showed better fit compared to the model without either (Model 7) and the model with only ICE (Model 8). The out-of-sample fit of the two-attribute SSH-based models was slightly better than that of the three-attribute SSH-based model (Model 9 versus Model 3). The results suggest that the two-attribute Pareto-optimal choice design had a small predictive advantage over the three-attribute design—likely due to more choice data per person.

We also tested the model involving only the dyadic part of the data (parts 3 and 4; Study 1A) to determine whether it is necessary to collect individual-level data in addition to dyadic data (parts 1–4; Study 1A). Table 3 shows that the SSH-based model involving both individual and dyadic data had a better out-of-sample fit than the model involving only the dyadic data (Model 10 versus Model 3),[7] indicating that individual data help improve model fit. Furthermore, the exclusion of the ICE effect from the model hurt the out-of-sample fit (Model 3 versus Model 11).

4.1.4. Estimation Results. The preference estimates in Table 4 reveal that, with all else being equal, respondents, on average, preferred printers that are faster, sharper, and cheaper. The preferences were nonlinear; for example, evidence suggested diminishing marginal utility at higher speed levels. Because respondents were paired with each other randomly, we did not expect the influence parameter to be different from 0.5 (equal influence), which was exactly what we found.

Table 5 reports the posterior means and standard deviations for the individual and dyadic compromise effect parameters. Both ICE and DCE were positive and significant, suggesting the existence of individual, and more importantly, dyadic compromise effect. Evidence from the KNS model (Model 4, Table 3) and the

Table 4. Study 1A Parameter Estimates: Preference and Influence

	Speed (pages/minute)		Resolution (dots/inch)		Price ($)	
	Level	Estimate	Level	Estimate	Level	Estimate
Preference ($\bar{\beta}$)	15	7.1 (1.4)	600 × 300	7.2 (1.1)	619	2.3 (1.4)
	20	9.3 (1.2)	600 × 600	10.0 (1.2)	519	6.3 (1.5)
	25	11.8 (1.5)	900 × 600	17.6 (1.3)	419	10.4 (1.2)
	30	14.5 (1.4)	900 × 900	22.4 (1.4)	319	18.3 (1.3)
	35	18.0 (1.4)	1200 × 900	25.3 (1.4)	219	20.8 (1.5)
	40	18.7 (1.7)	1200 × 1200	27.0 (1.4)	119	25.7 (1.6)
Influence ($\bar{\theta}$)	0.55 (0.10)		0.60 (0.09)		0.58 (0.08)	

Notes. The table shows posterior means along with posterior standard deviations in parentheses. Parameters $\bar{\beta}$ and $\bar{\theta}$ are the hyperparameters for β and θ. See the web appendix for complete technical details.

Table 5. Study 1A Parameter Estimates: Two-Attribute vs. Three-Attribute Design

			Scale
Three-attribute compromise sets	ICE ($\bar{\gamma}$)	7.8*	0.051
		(1.5)	(0.0042)
	DCE ($\bar{\tau}$)	22.4*	0.033
		(9.7)	(0.0049)
Two-attribute compromise sets	ICE ($\bar{\gamma}$)	9.2*	0.051
		(1.4)	(0.0042)
	DCE ($\bar{\tau}$)	12.2*	0.033
		(4.4)	(0.0049)

Notes. The table shows posterior means along with posterior standard deviations in parentheses. Parameters $\bar{\gamma}$ and $\bar{\tau}$ are the hyperparameters for γ and τ. See the web appendix for complete technical details.

*Indicates significance at the 5% level for ICE and DCE parameters.

Nash model (Model 6, Table 3) supported the presence of ICE and DCE as well (see the web appendix, Tables B and C), indicating that this result is robust to an alternative model specification and utility aggregation method. The posterior means from the two-attribute versus three-attribute SSH-based models are not significantly different from each other, although the two-attribute design estimates are more precise.

Our primary goals in Study 1 was to test for the presence of the DCE in a lab setting using the proposed statistical model. Next, in Study 2, we tested for DCE using intact dyads. We did so in a setting that involved husbands and wives making an important dyadic life decision: retirement planning. We designed the study to estimate the dyadic compromise effect, its association with the individual compromise effect, and factors that could mitigate it.

4.2. Study 2

We selected retirement planning as the context for our research based on a series of in-depth interviews with financial advisors that revealed that this category has a high dyadic relevance for married couples. Consistent with our decision to focus on retirement planning, LPL Financial (2012, p. 4), a company that serves more than 14,000 financial advisors nationwide, noted the following in one of its white papers.

> Couples are the bread and butter of the financial advisory business, but the way that they relate to advisors is changing. It is no longer as common for one partner to take the lead and make the decisions. Today's couples are more likely to take a collaborative approach to financial planning. Couples also count on each other for financial advice. Fifty-five percent of the people we surveyed said a spouse or partner was their top source of financial advice, well ahead of financial professionals (42%), friends (19%) and adult children (14%).

Indeed financial advisors are trained to balance the needs of each member when working with couples (UBS 2014).

Retirement plans are typically managed by employers, but employees, husband–wife dyads in our study, select the plan best aligned with their family's financial goals. Retirement planning is a particularly interesting category for the purpose of this research because significant gender differences exist in investment behavior (for a review, see Hira and Loibl 2008), in factors such as risk tolerance and need for investment simplicity. It is also an excellent category to study compromise effects, as shown by Benartzi and Thaler (2002), who found that participants perceived the portfolio of the median participant to be more attractive than the one they chose for themselves. This was even true for those who rejected a portfolio customized for them by experts.

4.2.1. Participants and Procedure. The study was completed by 169 married couples recruited with the help of C&R Research and Chamberlain Research. To qualify for this research, at least one spouse was required to have a retirement account. The respondents were also required to have all their retirement in defined contribution plans (e.g., IRA or 401(k)) in which they were responsible for selecting the types of investment in their accounts. Their household income had to be above \$50,000 based on our assumption that a sizeable retirement investment will likely result in greater task involvement. Each couple was paid \$25–\$40 for completing the survey.[8]

To ensure good-quality data, we dropped dyads where an individual exhibited "straight lining behavior" and gave the same rating to every conjoint profile (Baker et al. 2010, p. 757). This resulted in usable data from 158 couples. Among the 158 couples, both spouses had a retirement account in 101 (64%) families. Only the husband had a retirement account in 47 (30%) families, while only the wife had a retirement account in the remaining 10 (6%) families. A large majority (79.3% wives and 81.7% husbands) were between 35 and 55 years old, and the couples had an average of 3 children. The average annual household income was \$101,183. Both husbands and wives indicated low expertise in investment matters (husbands' average = 3.20 on a 1–7 scale; wives' average = 2.36) with wives rating themselves lower ($p < 0.05$).

Respondents who met the inclusion criteria were contacted to schedule a time to conduct the study in their homes. The study was set up such that the respondents could finish it online. To ensure that the respondents paid enough attention to the survey and to avoid any confusion, we called each dyad at the scheduled time to give them an overview of the survey. We also left a phone number in case they had any questions while taking the survey. The fieldwork of the study was completed over a three-month period.

The survey followed the structure outlined in Table 1. Each spouse completed individual tasks (part 1 and 2) that helped assess their context-independent preference and individual compromise effect—they completed 10 conjoint-rating tasks and 18 Pareto-optimal choice tasks. Then, if the wife had a retirement account, the dyad jointly finished a choice task followed by a conjoint-rating task (part 4 and 3, Table 1) for the wife's account. These two tasks allowed us to assess the attribute-specific influence of each member and the dyad's compromise effect for the wife's account. Next, if the husband had a retirement account, the dyad repeated the dyadic tasks (part 4 and 3, Table 1) for the husband's account. We also measured a variety of individual-level variables such as expertise in financial investment.

To investigate how the number of options in the Pareto-optimal choice set affected the individual and dyadic compromise effects, we included two different set sizes: five-option (large set size) and three-option choice sets (small set size). This is a within-subject design: Each individual provided choice data for the large-size as well as small-size choice sets (9 each, for a total of 18 choice sets). Similarly, each dyad provided choice data for the large-size as well as small-size choice sets (total of 18 choice sets). Filler questions were included among the Pareto-optimal choices.

To identify important attributes for financial investments, we interviewed several financial advisors before the study. They identified three such attributes that draw the most attention among investors: return, risk, and expense ratio. We define return as "the historical average annual return over the last 20 years" and risk in terms of "gain-loss swing over the last 20 years." Expense ratio is a percentage measure of the costs to operate a mutual fund typically obtained by dividing annual operating expense by the average dollar value of the assets. Return and risk levels were chosen based on historical performance data of various asset mixes from financial service companies such as Fidelity and Vanguard. The lowest return (5.39%) and lowest risk (15% to −1%) levels were based on the asset mix with 0% in stocks. At the other extreme, the highest return (10.13%) and highest risk (36% to −17%) levels were based on the asset mix with 100% in stocks (Vanguard Web).[9] The expense ratio ranged from 0.5% to 1.4% and was based on the market rates. There were four levels per attribute. Figure C in the web appendix provides an example of the ratings-based conjoint task used to assess context-independent preference.

For the Pareto-optimal choice sets, each option was described in terms of pairs of attributes. For the three attributes there were three possible pair combinations: {(return, risk); (return, expense ratio); (risk, expense ratio)}. For each combination, such as risk and expense ratio, three five-option (large set size) and three three-option choice sets (small set size) were created. There were 18 Pareto-optimal choice sets: 3 (choice sets per combination) × 3 (combinations) × 2 (set size). Figure D in the web appendix shows an example of a small set size (i.e., three options) choice question.

Across the three-option and five-option Pareto-optimal choice sets were nine levels for each attribute. To illustrate, there were five levels for the three-option choice sets (e.g., return levels 5.39%, 6.92%, 8.22%, 9.29%, and 10.13%). For the five-option choice sets, there were seven levels (e.g., return levels 5.39%, 6.46%, 7.36%, 8.22%, 9.02%, 9.59%, and 10.13%). Three levels were common for the three-option and five-option sets (5.39%, 8.22%, and 10.13%). Therefore, altogether, there were nine (five in the three-option set plus seven in the five-option set minus three overlap) levels for each attribute. It is difficult to include all nine levels in the conjoint without increasing the number of rating tasks per person. As a result, we included four levels (e.g., return levels 5.39%, 7.36%, 9.02%, and 10.13%) for each attribute in the ratings-based conjoint exercise and interpolated the estimates for the remaining levels. In Study 1, the two-attribute design has the best in-sample and out-of-sample fit. Study 2 relies on a two-attribute design as well, and we did not include the three-attribute design in this study.

4.2.2. Model-Free Results. Table 6 shows the market shares of choice options in five-option Pareto-optimal choice sets. We found that E's market share was 26.1% when it was an extreme option in set 1, but its shares were 32.4% and 36.9% in sets 2 and 3, respectively, when it was an intermediate option. This 8.6% difference provides model-free evidence in support of the compromise effect in dyadic choices ($p < 0.05$). A similar conclusion can be made ($p < 0.05$) when we compare market share of alternative C across the three sets (9%, 13.5%, and 26.1%; difference = 10.8%).

For the return–expense ratio pair, the compromise effect difference measures were 10.8% ($p < 0.05$) for alternative C and 5.9% for alternative E. For the risk–expense ratio pair, the compromise effect difference measures were 8.6% ($p < 0.05$) for alternative C

Table 6. Evidence of DCE (Wives' Accounts)

	Return	Risk	Set 1 (%)	Set 2 (%)	Set 3 (%)
Alternative	Average annual return over the last 20 years (%)	Gain–loss swing over the last 20 years			
A	5.39	15% to −1%	3.6		
B	6.46	17% to −2%	9.0	4.5	
C	7.36	20% to −4%	26.1	13.5	9.0
D	8.22	23% to −7%	35.1	33.3	19.8
E	9.02	27% to −10%	26.1	32.4	36.9
F	9.59	31% to −13%		16.2	18.0
G	10.13	36% to −17%			16.2

Table 7. Model Comparison—Wives' Accounts

	Model description						In-sample fit[a]		Out-of-sample fit[b]	
No.	No. of attributes (choice design)	Compromise effect model	ICE	DCE	Utility aggregation	Data from parts	LMD	DIC	Hit rate (%)	MAE
1	2	No	No	No	Linear	1–4	−5,023	24,909	23.3	0.104
2	2	SSH	Yes	No	Linear	1–4	−4,392	19,372	33.2	0.096
3	2	SSH	Yes	Yes	Linear	1–4	−4,281	18,568	37.4	0.094
4	2	KNS	Yes	Yes	Linear	1–4	−4,348	21,436	30.7	0.097
5	2	SSH	No	Yes	Linear	3–4	−1,334	5,948	33.5	0.094
6	2	SSH	No	Yes	Linear	1, 3, 4	−4,858	21,461	33.5	0.094

[a]In-sample fit was based on likelihood calculation for seven choice tasks.
[b]Out-of-sample fit was based on two holdout choice tasks.

and 2.7% for alternative E. Thus, the model-free results suggest that the dyads were prone to a compromise effect when making joint choices. The pattern of results reported in Table 6 also persists for the husbands' accounts.

4.2.3. Model Fit. Table 7 displays model comparison results for the large set size (five-option) data for wives' accounts for the SSH-based model ($n = 111$). Similar results were found for husbands' accounts as well ($n = 148$). As in Study 1, we found that incorporating individual-level compromise effects resulted in better in-sample and out-of-sample fit (Model 2 versus Model 1). Incorporating dyadic compromise effect resulted in further gains in in-sample and out-of-sample fit (Model 3 versus Model 2).

The SSH-based model fits the data better than the KNS-based model (Model 3 versus Model 4). The overall pattern of results provides strong evidence supporting the presence of DCE. Finally, as in Study 1, out-of-sample fit results shown in the last two rows[10] of Table 7 show that the SSH-based model involving both individual and dyadic data outperformed the models relying only on the dyadic data (Model 3 versus Model 5). Excluding the ICE effect from the model hurt the out-of-sample fit (Model 3 versus Model 6).

4.2.4. Estimation Results. The individual preference and influence estimates for the SSH model are reported in Table 8. The general pattern of preference estimates is reasonable. On average, both husband and wife groups exhibited great sensitivity to each one of the three included attributes and in the predicted direction: There was greater preference for higher return, lower risk, and lower expense ratio. Wives, on average, had significantly less influence ($\bar{\theta} < 0.5$) than the husbands, although they had slightly greater influence on their own accounts than their husbands' accounts. This pattern of results is consistent with a recent survey that revealed wives to be less involved in their retirement finances than their husbands.[11]

Table 9 shows the estimates of the individual and dyadic compromise effects for the large and small set size cases. The top two rows report the individual and dyadic compromise effect parameter estimates for the wives' accounts; the bottom two rows are those for the husbands' accounts. For the wives' accounts, in the large set size case, the husband and wife, on average, were prone to the individual compromise effect (wife, 15.7; husband, 10.2) and the dyadic compromise effect (dyad, 9.6). Thus, Study 2 provides model-based evidence in support of the DCE. Interestingly, in the small set size

Table 8. Preference and Influence Parameter Estimates

	Return			Risk			Expense ratio		
	Level (%)	Wife	Husband	Level	Wife	Husband	Level (%)	Wife	Husband
Preference ($\bar{\theta}$)	7.36	11.6	15.3	27% to −10%	9.2	6.3	1.1	1.5	1.9
		(1.4)	(1.5)		(1.7)	(1.4)		(1.6)	(1.2)
	9.02	19.2	22.4	20% to −4%	19.4	14.5	0.8	10.8	11.1
		(2.1)	(2.0)		(2.8)	(2.2)		(1.9)	(1.9)
	10.13	19.5	26.9	15% to −1%	19.3	16.8	0.5	14.8	14.2
		(2.3)	(2.5)		(3.1)	(2.7)		(2.1)	(2.1)
Wife's influence on own account ($\bar{\theta}$)		0.56			0.49			0.47	
		(0.08)			(0.09)			(0.08)	
Wife's influence on husband's account ($\bar{\theta}$)		0.34			0.34			0.36	
		(0.05)			(0.05)			(0.05)	

Notes. The table shows posterior means along with posterior standard deviations in parentheses. Parameters $\bar{\beta}$ and $\bar{\theta}$ are the hyperparameters for β and θ. See the web appendix for complete technical details.

Table 9. Individual and Dyadic Compromise Effects

		Large set size (five options)		Small set size (three options)		Scale
		Wife	Husband	Wife	Husband	
Wives' accounts	ICE ($\bar{\theta}$)	15.7*	10.2*	8.0*	4.4*	0.046
		(3.1)	(2.8)	(1.7)	(1.7)	(0.0038)
	DCE ($\bar{\tau}$)	9.6*		2.1		0.039
		(3.2)		(1.9)		(0.0051)
Husbands' accounts	ICE ($\bar{\gamma}$)	21.6*	7.2*	8.9*	2.6*	0.037
		(3.3)	(3.0)	(1.7)	(1.7)	(0.0026)
	DCE ($\bar{\tau}$)	4.2*		−1.4		0.032
		(2.8)		(1.4)		(0.0039)

Notes. The table shows posterior means along with posterior standard deviations in parentheses. Parameters $\bar{\gamma}$ and $\bar{\tau}$ are the hyperparameters for γ and τ. See the web appendix for complete technical details.

*Indicates significance at the 5% level for ICE and DCE parameters.

case, the magnitude of the individual compromise effect was smaller (wife, 8.0; husband, 4.4). The dyadic compromise effect (dyad, 2.1) in the small set size case was not significantly different from zero.

The overall pattern of compromise effect results for the husbands' accounts (bottom two rows of Table 9) is identical to what we found earlier. The large set size case uncovered significant individual and dyadic compromise effect parameters (wife, 21.6; husband, 7.2; dyad, 4.2). Also, as before, in the small set size case, the magnitude of the individual compromise effect was smaller, and the dyadic compromise effect was not significantly different from zero. This result supports the claim that a smaller number of options can reduce both individual and dyadic compromise effects. Furthermore, evidence from the KNS model (Model 4, Table 7) follows a similar pattern (web appendix, Table C), indicating that this result is robust to an alternative model specification. One possible theoretical rationale for an increased compromise effect for larger set sizes is the greater need to rely on the heuristic to select the "average" option when confronted with overchoice. Buyers may experience an enhanced need to minimize postdecision regret when confronted with more options.

The above finding differs from what KNS found. In their paper, ICE was found to be smaller in a choice set with more options. It is difficult to compare the results across the two papers, although some differences are worth noting. First, KNS compared ICE across two different studies involving two distinct samples (travelers at an airport and students). Second, in the KNS paper, the three-option design was described on two attributes, and the five-option design was described on four attributes. By contrast, both three- and five-option designs are described on three attributes in our paper, and there are no sample differences. In light of the conflicting results across KNS and our paper, additional research may be required to help resolve the discrepancy.

We also detected a difference in ICE by gender in this category. Table 9 indicates that wives, on average, are more prone to individual compromise effects than husbands for both large and small set size cases. For example, for husbands' accounts in the large set size case, the posterior mean of the wives' individual compromise effect (21.6) was higher than that of the husbands' individual compromise effect (7.2). The gender effect is likely driven by wives' lower expertise in financial investment (wives, mean = 2.36 on a 1–7 scale; husbands, mean = 3.20).

In addition, we found that the dyadic compromise effect was smaller for husbands' accounts compared to wives' accounts (e.g., for the large set size case, it was 4.2 versus 9.6). The variance–covariance matrix of the ICE and DCE parameters revealed an interesting pattern. For the wives' accounts, the wives' ICE was highly correlated with DCE (0.95), while the husbands' ICE was moderately correlated with DCE (0.44). Along the same lines, for the husbands' accounts, the husbands' ICE was highly correlated with DCE (0.84), while the wives' ICE had a lower correlation with DCE (0.70). Therefore, an interesting finding from Study 2 is that the individual compromise effect tendency of a group member with a greater stake in the decision is likely to persist as DCE in the joint choice setting. This finding could be driven by two factors. First, an individual who tends to prefer the intermediate option because of the compromise effect is likely to push for selecting the compromise option in a dyadic choice decision as well. Second, account ownership is likely to make the account owners more vocal and assertive about selecting the compromise option. Table 8 suggests that a wife has more influence on her account than on her husband's account, and a husband has more influence on his account than his wife's account.

In summary, in Study 2, we found evidence of model-free and model-based dyadic compromise effects. Model-based evidence in support of DCE is robust to an alternative model specification. A model that incorporates the DCE also fits the dyadic choice data better. In our sample, wives were, on average, more prone to the ICE than their husbands, which was likely due to the former's lower perceived expertise. We found evidence that the ICE is associated with the DCE. The individual compromise effect of the group member with a greater stake in the choice decision appears to persist as a dyadic compromise effect in a joint choice setting.

5. Discussion

When groups make choices (e.g., committee decisions) it is plausible that the tendency to select the intermediate option may be at play. The purpose of this paper is to investigate compromise effects in such settings. For empirical convenience, we test joint compromise effects in a dyadic setting, although the general ideas we propose apply to larger groups as well.

5.1. Findings

We conducted two studies to test the proposed model and answer our research questions. We found strong model-free and model-based evidence to support the presence of the dyadic compromise effect. In Study 1, we tested the proposed model using student subjects and found ICE and DCE in the printer category. We also found that the collection of individual data, in addition to the dyadic data, helped improve the model fit. In Study 2, we examined the dyadic compromise effect in a setting in which married couples were asked to make retirement investment choices. As in Study 1, a model incorporating DCE provided a better fit than a model that did not incorporate it. We also found that greater ICE was associated with greater DCE. This association was stronger for the group member with a greater stake in the choice decision. Our findings suggest that choice sets with fewer options may reduce the DCE. Furthermore, the education of the market segments vulnerable to compromise effects (e.g., women in the context of retirement planning from Study 2) may be an effective method to mitigate the DCE.

5.2. Implications for Financial Planning

Trends in private pension provisions[12] show that an increasing proportion of pension plans are of the defined contribution type. This type of plan, compared to a defined benefit plan, shifts investment risk from plan sponsors to plan participants. As more plans require participants to make their own allocation decisions, investor choice sensitivity to options presented to them could imply significant losses in investor welfare (Brennan and Torous 1999; Benartzi and Thaler 2001, 2002). Although most plans provide information materials to participants, more education on investment principles and financial planning may help reduce the DCE when families select a retirement plan. In addition to more education, it may help families further if the choices given to them are simplified.

5.3. Limitations and Future Research

Rooderkerk et al. (2011) (hereafter, RVB) proposed an alternative approach to model the compromise effect. Unlike KNS and SSH, who adopted a two-stage model to uncover compromise effects, RVB used a one-stage approach relying on choice data for a single experiment to uncover both preferences and compromise effects. A conceptual distinction between RVB's approach and KNS's and SSH's approaches is that the former conceptualized compromise effects at the level of the alternative, whereas the latter did so at the level of an attribute. It may be instructive to recast our model relying on the one-stage approach and test for the presence of ICE and DCE at the alternative level.

A methodological challenge in the one-stage approach is how to best design a choice experiment that uncovers the compromise effect parameter in addition to the preference parameters. The traditional choice designs are constructed to estimate only the latter efficiently. This presents a challenge to design a choice experiment that efficiently estimates *all* parameters in the RVB model. Along the same lines, in the two-stage approach we adopted, the ICE (and DCE) parameters are estimated based on data from Pareto-optimal choice sets. For this model as well, future research could offer guidance on how to optimize the design of choice sets that estimate compromise effects efficiently.

Guided by the notion to induce truth telling in experiments, economists often adopt the Becker–DeGroot–Marschak (BDM) mechanism (Becker et al. 1964). Experiments that study ICE and DCE should attempt to incorporate the BDM-type incentive alignment mechanisms when possible. In marketing, methodologies to implement incentive alignment at the individual level exist (Wertenbroch and Skiera 2002, Ding 2007), but they have not been tested in contexts that involve groups of individuals. In our experimental context, it was difficult to implement incentive alignment because the study design involved individual (part 2) as well as dyadic (part 4) choice. Future research should investigate how extant incentive alignment methods could be adapted to contexts that involve multiple individuals.

By contrast with most compromise effect studies, a unique aspect of our study design is that we have repeated choices. This, in principle, allows us to investigate shifts in DCE over time. In our empirical investigation, we compared DCE measures based on earlier choices versus later choices and found no evidence to support temporal shifts in DCE: none of the differences between "early" and "late" groups were statistically significant. One limitation of our analyses was that the sample size/cell was small. The small sample size limited our ability to detect temporal patterns in DCE, if any, precisely. Future research could investigate temporal patterns in compromise effects by using a larger sample size in the context of repeated choices.

Finally, in Study 2, for the Pareto-optimal choice section of the design, we relied on a subset of all of the attribute levels. This likely forced the respondents to impute the value they attach to the missing attributes or levels that they were not asked to evaluate. Future research could account for such a possibility by building on the ideas suggested by Bradlow et al. (2004).

Acknowledgments

This paper is based on the first author's doctoral dissertation at the University of Wisconsin–Madison. Support for this research was provided by the University of Wisconsin–Madison Office of the Vice Chancellor for Research and Graduate Education with funding from the Wisconsin Alumni Research Foundation. The authors thank Paul Metz of C+R Research and Sharon Chamberlain of Chamberlain Research Consultants for their generous help with data collection. The authors also thank Qing Liu and Anocha Aribarg for their helpful comments. The paper greatly benefited from conversations about the financial investments industry with Michael Bell (UBS Financial Services) and Nate Hedden (Musser Capital Advisors).

Endnotes

[1] This is the normalized contextual concavity model proposed by KNS. It was also their best fitting model.

[2] This is simply to conserve space. Empirically, we find that the SSH-based model fits better than the KNS-based model. Model specification changes and results for the KNS-based model are reported in the web appendix.

[3] We thank a reviewer for suggesting the MA specification. In the context of our data we find that EA fits slightly better than the MA model. The model comparison between EA and MA models is included in the web appendix. The acronyms SSH and EA are interchangeable. The former refers to the authors and the latter to the model they use in their paper.

[4] We thank an anonymous reviewer for suggesting the last three comparisons.

[5] MAE = | Actual market share of an alternative across respondents − Model based predicted market share | .

[6] The LMD measure can sometimes be numerically unstable. Per a reviewer's suggestion, we estimated each model 10 times. We then used the Mann–Whitney *U* test (nonparametric independent sample test) to determine if the proposed SSH-based model consistently outperformed the other models on the LMD criterion. The overall pattern of results reported in Table 3 remains unchanged.

[7] Only out-of-sample fit comparisons are relevant for these comparisons.

[8] Financial incentives varied by vendor.

[9] See Vanguard (2012).

[10] Only out-of-sample fit comparisons are relevant for these comparisons.

[11] See Business Wire (2011).

[12] See Employee Benefits Security Administration (2016).

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