The Dyadic Compromise Effect

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ABSTRACT

The exclusive focus of existing research on the compromise effect has been on the individual. This paper investigates compromise effects in a dyadic choice setting. We investigate whether dyads exhibit compromise effects, factors that may moderate this effect and strategies that could be used mitigate it. We build a statistical model of dyadic choice that incorporates individual preference and influence and accounts for compromise effects—individual and dyadic—by transforming context-independent utility into a more concave context-dependent utility. We conducted two studies to test our proposed models empirically. Study 1 begins with an investigation of individual compromise effect (ICE) and its moderators. In Study 2 we test for the presence of dyadic compromise effect (DCE) in which married couples are asked to make retirement investment choices. We find strong empirical evidence in support of DCE—models incorporating DCE provide better fit than models that do not. We find that ICE tendency of a group member with a greater stake in the decision results in greater DCE. Our findings suggest that choice sets with fewer options mitigate DCE. Further, education of segments most vulnerable to compromise effects (e.g. women in the context of retirement planning) could be effective to mitigate DCE.

Keywords: Joint Choice, Groups, Bayesian, Heterogeneity, Financial Planning
The compromise effect has been studied extensively in marketing—its basic prediction is that an alternative will gain share 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 selection of the intermediate option is easier to justify, less likely to be criticized (Simonson 1989) and is consistent with loss aversion (Simonson and Tversky 1992). Since Simonson’s seminal paper first illustrated this effect, marketing scholars have investigated antecedents and moderators of the compromise effect (e.g. Dhar, Nowlis and Sherman 2000; Nowlis and Simonson 2000; Drolet 2002; Chernev 2004) and incorporated it in formal choice models (Kivetz, Netzer and Srinivasan 2004; Sharpe, Staelin and Huber 2008; Roederkerk, van Heerde and Bijnvill 2011).

The exclusive focus of existing research on the compromise effect has been on the individual. Another context where the compromise effect may be highly relevant is when a group of individuals make a joint decision. Examples include family purchases (e.g. for an appliance) or organizational buying (e.g. for hospital equipment). In the simplest of scenarios consider a husband-wife dyad selecting a dishwasher at a Sears store. In this example it is reasonable to ask whether the individual tendency to select the intermediate option (i.e. the one with average quality, average price) is mitigated or magnified in the joint choice context. Extant literature provides mixed guidance on how to answer this question. On the one hand, the compromise effect could be enhanced in the joint choice context because the intermediate option may be easier to justify and less likely to be criticized by each group member. On the other hand, greater deliberation and pooled knowledge may help the dyad become more objective and less susceptible to selecting the easy-to-defend intermediate option. The purpose of this paper is to investigate compromise effects in a dyadic setting. We answer three specific questions: (i) Do
dyads, like individuals, exhibit the compromise effect? (ii) If yes, are there factors that moderate the dyadic compromise effect? (iii) Finally, could the dyadic compromise effect be mitigated so that the choices a dyad makes are more aligned with its true preference?

In this paper we define the term dyadic compromise effect (DCE) as a dyad’s tendency to select an intermediate option in a joint choice decision. The dyadic choice setting presents significant 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 separately from their preference. Third, the individual compromise effect (ICE) needs to be separated from dyadic compromise effect. Finally, it is important to recognize heterogeneity in compromise effects that likely vary across individuals and dyads. To overcome these challenges we rely on two streams of literature in marketing in our investigation: statistical models of group choice and individual level compromise effects. Specifically, we build upon statistical models that incorporate the individual compromise effects (Kivetz, Netzer and Srinivasan 2004; Sharpe, Staelin and Huber 2008) and joint choice (Arora and Allenby 1999).

In our models, the ICE is captured by transforming context-independent utility into a more concave context-dependent utility as suggested by Kivetz, Netzer and Srinivasan (2004) and Sharpe, Staelin and Huber 2008. The basic premise is that that utilities of attribute levels are measured at a global (context independent) level with methods such as ratings based conjoint analysis. The global utility functions can be linear, concave or convex. The models then transform the global, context independent utilities into context dependent utilities according to the local context (i.e. based on options in a choice set). Stated differently, context dependent
preference is measured in a local choice context; context independent preference is measured at a global level and does not involve a choice decision. In order to capture the DCE, we add another layer of concavity to the dyad’s preference in a model that incorporates individual preferences as well as their influence (Harsanyi 1955). Our full model of dyadic choice incorporates individual preference and influence and accounts for compromise effects—individual and dyadic—by transforming context-independent utility into a more concave context-dependent utility.

Two studies were conducted to test our proposed models. In Study 1, we begin with an investigation of ICE and its moderators. In Study 2 we test for the presence of DCE in a setting in which married couples are asked to make retirement investment choices. We find strong empirical evidence in support of DCE—a model that incorporates DCE provides better fit than a model that does not. We find that greater ICE is associated with greater DCE. Importantly, the ICE tendency of a group member with greater stake in the decision appears to result in greater DCE. Because compromise effects result in dyads selecting options not entirely consistent with their true context independent preference, we investigate means to mitigate them. Our findings suggest that choice sets with fewer options help reduce DCE. Further, education of market segments most vulnerable to compromise effects (e.g. women in the context of retirement planning from our study 2) may be an effective method to mitigate DCE.

The remainder of the paper is organized as follows. We first review related literature and describe our conceptual framework. We then lay out our modeling framework. Next we present two studies where for each study we provide detailed description of our experimental design, data collection procedure, and key empirical findings. We close with a discussion about our contributions and future research.
CONCEPTUAL BACKGROUND

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

Individual Compromise Effect

Following Simonson (1989) we illustrate the compromise effect below (Figure 1). Consider alternatives A, B, C and D, which vary on two dimensions – attribute $m$ and $n$. The main finding pertaining to the compromise effect is that 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\}.

The compromise effect has been largely explained as a context effect in terms of constructive preferences (e.g., Bettman, Luce and Payne 1998). 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. In line
with the constructive preference argument, two main causal explanations are proposed in the literature (Gourville and Soman 2007). First, Simonson (1989) argues that the selection of the intermediate option is easier to justify than an extreme option and less likely to be criticized. He reasons that decision makers who expect to be evaluated by others are more likely to show the compromise effect. The selection of a compromise alternative is the safest when the evaluators have uncertain global preferences. A compromised choice can reduce the conflict associated (Sheng, Parker and Nakamoto 2005) with giving up one attribute for another (e.g. selecting a low price, high quality product) and can be justified by arguing that it combines both attributes (e.g. selecting an average price, average quality product). Second, Simonson and Tversky (1992) explain the compromise effect by the theory of “loss aversion” or “extreme aversion”. They argue that consumers are likely to evaluate the advantages and disadvantages of the products in the choice set in relation to each other. The disadvantages of the extreme options loom larger than the advantages, leading to the compromise effect.

Factors that moderate the compromise effect could be divided into two broad categories: characteristics of the decision makers and those of the decision tasks. Relevant personal characteristics include expertise, risk aversion and need for uniqueness (Sheng, Parker and Nakamoto 2005, Bettman, Luce and Payne 1998, Carlson and Bond 2006, Huber and Puto 1983, Simonson and Tversky 1992, Chernev 2004, Sinn et al. 2007, Simonson and Nowlis 2000). Besides person specific factors, characteristics of the decision tasks could also play a role in moderating the compromise effect. For example, the more symmetric the attribute-importance structure—that is, all attributes are roughly equally important—the more difficult the decision is and the more likely a compromise option will be attractive to the consumer (Sheng, Parker and Nakamoto 2005).
Dyadic Compromise Effect

Dyadic compromise effect refers to a dyad’s tendency to select an intermediate option in a joint choice decision. Extant literature provides limited guidance on whether the compromise effect is enhanced in such joint choice contexts. On the one hand, research reveals that groups with heterogeneous prior individual judgments have more accurate joint judgment than do individuals (Corfman and Kahn 1995). The premise being that group members with different perspectives are more likely to engage in pooling information and discussing differences to come to a better understanding of the judgment task. The errors in individual judgment may also be diminished as a result of such group interaction. The resulting higher product familiarity from knowledge exchange among group members could lead to lower proneness to the dyadic compromise effect. On the other hand, research also shows that groups tend to exaggerate individual biases (Hinsz, Tindale and Nagao 2008; Smith, Tindale and Steiner 1998 and Whyte 1993). Further, when there is an overt need to justify the choice to others, as may be the case in a joint choice setting, people may tend to choose the intermediate option because it does not possess any extreme features that are likely disapproved by some group members.

Conceptually and methodologically several aspects of the joint choice setting make it difficult to demonstrate the presence of dyadic compromise effects. First, we need to account for differences in preference between the two individuals in a dyad. Second, individual level compromise is likely present in a joint choice context and needs to be incorporated. Third, individuals in the dyad may have differential influence in the joint choice decision. In the following illustration we highlight these different aspects of joint choice decisions and the role dyadic compromise effect may play. The subsequent statistical model accounts for these specific aspects of a joint choice decision.
Illustration of the Dyadic Compromise Effect

In this hypothetical example, a husband and a wife choose among three financial investment portfolios varying on risk and return. The example is consistent with the normalized contextual concavity model in Kivetz, Netzer and Srinivasan (2004). 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). The top panel of figure 2 shows the context independent utility function for the wife in this example. This is shown by the dashed line. As suggested by Kivetz, Netzer and Srinivasan (2004) context independent utility is based on an evaluation of one alternative at a time; 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) and that for return (more is better) is upward sloping. Her total context independent utility for options A, B and C, also shown as 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 and 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). As a result of the compromise effect, the intermediate option B gains utility and becomes as attractive as option A—she is likely to choose the circled options A or B as a result. For the husband in our example, the context independent and context dependent utility functions are shown in the second panel of figure 2. Like his wife, the husband also prefers a low-risk investment with low return and because of individual compromise effect is likely to choose the circled options A or B (they have equal utility for him also).
Figure 2: Graphical Illustration of the Dyadic Compromise Effect

**Wife’s Utility (Individual Compromise Effect Only)**

- **Risk**
  - Option A
  - Option B
  - Option C

- **Return**
  - Option A
  - Option B
  - Option C

- **Total Utility - Wife**
  - Option A
  - Option B
  - Option C

**Husband’s Utility (Individual Compromise Effect Only)**

- **Risk**
  - Option A
  - Option B
  - Option C

- **Return**
  - Option A
  - Option B
  - Option C

- **Total Utility - Husband**
  - Option A
  - Option B
  - Option C

**Dyadic Utility (Individual Compromise Effect Only)**

- **Equal Influence**

- **Risk**
  - Option A
  - Option B
  - Option C

- **Return**
  - Option A
  - Option B
  - Option C

- **Total Utility - Joint**
  - Option A
  - Option B
  - Option C

**Dyadic Utility (Individual and Dyadic Compromise Effect)**

- **Risk**
  - Option A
  - Option B
  - Option C

- **Return**
  - Option A
  - Option B
  - Option C

- **Total Utility - Joint**
  - Option A
  - Option B
  - Option C
The third panel combines individual utilities to demonstrate what the dyad may choose collectively. In our example we combine context-dependent individual preferences assuming that each individual has equal influence in the joint choice. It shows that option A and B have the highest dyadic utility after the individual preferences are combined so the dyad may be indifferent between choosing option A or B. The fourth panel illustrates how dyadic compromise effect may play a role. The dyad’s utility of the middle option is higher as seen by the dotted line to capture the dyadic compromise effect. This could occur because each member of the dyad wants to avoid future criticism for selecting an extreme, much too conservative option A (lowest risk, lowest return). After the dyadic compromise effect is incorporated in the utility function option B enjoys a higher utility than option A (and C) and is therefore selected.

The above illustration demonstrates how dyadic compromise effect may manifest itself in joint choice decisions. It also illustrates the general complexity of the dyadic choice process. For example, although the preference correlation between the two members in our simple illustration is positive, it could also be negative. Similarly members’ relative influence could be unequal. Further the key pieces at the heart of joint choice decisions (individual preference, influence, individual compromise effect and dyadic compromise effect) are likely heterogeneous. Next we describe a statistical model that captures these different nuances of the dyadic choice process.

**DYADIC COMPROMISE EFFECT MODEL**

Consistent with the view that choice is a constructive process (e.g., Bettman, Luce and Payne 1998; Payne et al. 1992) consumers are assumed to modify their inherent preferences on-the-fly based on the local choice context. Bernatzi and Thaler (2002) highlight the importance of this idea in the context of financial investments where individual investors exhibit the tendency to select the middle option, partly because they do not have well-formed preferences. The models
capturing compromise effects typically decompose a product’s utility into a context-independent and a context-dependent component by transforming the context-independent utility into a more concave context-dependent utility (Kivetz, Netzer and Srinivasan 2004; Sharpe, Staelin and Huber 2008; Geyskens, Gielens and Gijsbrechts 2010; Roorderkerk, van Heerde and Bijmolt 2011). Kivetz, Netzer and Srinivasan (2004)—referred hereafter as KNS—capture the compromise effect with formal statistical models and we build upon their work to develop a model that captures the dyadic compromise effect. We rely on Arora and Allenby (1999) to model individual preferences and influence in a joint choice context.

**KNS Based Dyadic Compromise Effect Model**

We divide the model development part in the following subsections: context independent preference, context dependent preference, utility aggregation and dyadic compromise effect and parameter heterogeneity.

**Context-Independent Preference (Individual)**

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

$$ u_{ij} = \sum_{m} \sum_{k} u_{jmik} + \varepsilon_{ij} = \sum_{m} \sum_{k} x_{jmik} \beta_{imk} + \varepsilon_{ij} $$

where the error term $\varepsilon_{ij}$~Normal $(0, \sigma^2)$ and $\beta_{imk}$ is the context independent preference that is measured at global level with a method such as ratings based conjoint.

**Context-Dependent Preference (Individual)**

In equation (1) context independent preference $\beta_{imk}$ 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—the choice options they see. In the presence of such choice data the context-independent preference $\beta_{imk}$ is transformed into a more concave function through a concavity parameter $c_{im}$, which captures 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:

\begin{equation}
\beta_{imk}^S = \left(\beta_{i,m,\text{max}}^S - \beta_{i,m,\text{min}}^S\right) \times \left[\left(\beta_{imk}^S - \beta_{i,m,\text{min}}^S\right) / \left(\beta_{i,m,\text{max}}^S - \beta_{i,m,\text{min}}^S\right)\right]^{c_{im}}
\end{equation}

where

- $\beta_{imk}^S$ is the individual’s context-dependent preference of attribute level $k$ on attribute $m$ in choice set $S$.
- $\beta_{imk}^S$ is the individual’s context-independent preference of attribute level $k$ on attribute $m$.
- $\beta_{i,m,\text{min}}^S$ is the individual’s lowest preference on attribute $m$ in choice set $S$.
- $\beta_{i,m,\text{max}}^S$ 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 $c_{im} > 0$.

In equation (2), when $\beta_{imk} = \beta_{i,m,\text{min}}^S$, $\beta_{imk}^S$ is reduced to 0; when $\beta_{imk} = \beta_{i,m,\text{max}}^S$, $\beta_{imk}^S$ becomes $\beta_{i,m,\text{max}}^S - \beta_{i,m,\text{min}}^S$. Therefore, the context-dependent preferences for extreme levels on each attribute are not a function of the concavity parameter $c_{im}$. The concavity parameter $c_{im}$ can only 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, smaller or same valued context-dependent utility. If $c_{im} = 1$, the context-dependent preference is

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1 This is normalized contextual concavity model proposed by KNS. It was also their best fitting model.
\[ \beta_{imk}^s = \beta_{imk} - \beta_{i,m,min}^s \], which does not change \( \beta_{imk} \)'s relative utility compared to the two extreme levels. If \( 0 < c_{im} < 1 \), the utility becomes a more concave function compared to the context-independent utility function. In that case, \( \beta_{imk}^s > \beta_{imk} - \beta_{i,m,min}^s \). If \( c_{im} > 1 \), the function is convex, i.e., \( \beta_{imk}^s < \beta_{imk} - \beta_{i,m,min}^s \).

Alternative \( j \)'s context dependent utility can be written as

\[ u_{ij}^s = \sum_m \sum_k x_{ijk} \beta_{imk}^s + \epsilon_{ij} \]  

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

\[ \Pr(y_{is} = j) = \frac{\exp(b_i \sum_m \sum_k x_{ijk} \beta_{imk}^s)}{\sum_j \exp(b_i \sum_m \sum_k x_{ijk} \beta_{imk}^s)} = \frac{\exp(\sum_m \sum_k x_{ijk} \beta_{imk}^{s})}{\sum_j \exp(\sum_m \sum_k x_{ijk} \beta_{imk}^{s})} \]  

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, Louviere and Swait 1999). The term \( \beta_{imk}^{s} (= b_i \beta_{imk}^{s} ) \) is the context dependent preference adjusted for scale differences and can be interpreted in a manner similar to a logit model parameter.

**Utility Aggregation and Dyadic Compromise Effect**

Analogous to the individual level setup above, next we model dyadic context independent preference \( (\beta_{gmk}) \) and context dependent preference \( (\beta_{gmk}^s) \). Similar to the case of the individual, \( \beta_{gmk} \) is the dyadic context independent preference that is measured at global level with a method such as 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, Arora, and Bodur 2002). This utility aggregation model has been shown to outperform multiplicative models, Rawls model and models that minimize regret (e.g. Aribarg, Arora and Kang 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 ($\theta_{gm}$). Formally, let $i_1$ and $i_2$ denote individual members in the dyad and $g$ refer to the dyad, the dyadic preference $\beta_{gmk}$ is given by:

$$
\beta_{gmk} = \theta_{gm} \beta_{g,i,imk} + (1 - \theta_{gm}) \beta_{g,j,imk}
$$

That is, the dyadic preference is a weighted sum of context independent preferences of individuals. In this setup, an increase in the influence of member $i_1$ results in a decrease in the influence of member $i_2$. The parameter space of $\theta$ is often constrained to lie between 0 and 1 (Curry, Mensaco, and Van Ark 1991 and Krishnamurthi 1988) which ensures that group preference is a convex combination of individual member preferences. However, group preference may lie outside the convex hull defined by individual preferences—this is consistent with the group polarization phenomenon (Myers and Lamm 1976, Rao and Steckel 1991). Our specification of $\theta$ is without the $0 \leq \theta \leq 1$ constraint and is flexible enough to capture group polarization when present.

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

$$
\tilde{\beta}_{gmk} = \theta_{gm} \beta_{g,i,imk} + (1 - \theta_{gm}) \beta_{g,j,imk}
$$
The term \( \tilde{\beta}_{gmk} \) folds in individual compromise effects when a dyad is making a joint choice decision. Finally, when a dyad is confronted with a choice set its preference may change because of the dyadic compromise effect—the intermediate options may gain additional utility in the dyadic setting because of the local context. To capture this effect mathematically we transform the term \( \tilde{\beta}_{gmk} \) into a more concave function through a concavity parameter \( a_{gm} \), which captures the dyad-specific compromise effect. Similar to equation (2) the parameter \( \beta_{gmk}^S \) is the dyadic context dependent utility and \( a_{gm} \) captures the dyadic compromise effect.

\[
\beta_{gmk}^S = \left( \beta_{g,m,max}^S - \beta_{g,m,min}^S \right) \times \left[ \frac{\left( \beta_{gmk} - \beta_{g,m,min}^S \right)}{\left( \beta_{g,m,max}^S - \beta_{g,m,min}^S \right)} \right]^{agm}
\]

(7)

As in the case of individual compromise effect, \( a_{gm} \) adds a layer of concavity and captures the dyadic compromise effect of attribute \( m \) when \( 0 < a_{gm} < 1 \). For the purpose of estimation \( a_{gm} \) is reparameterized as \( \exp(a_{gm}) \) so that \( a_{gm} > 0 \).

Lastly, analogous the setup at the individual level, the group’s context dependent utility

\[
u_{gl}^S = \sum_m \sum_k x_{gimk} \beta_{gmk}^S + \epsilon_{gl}^S \]

and the probability that dyad \( g \) chooses alternative \( j \) in the context \( S \) follows a multinomial logit model with a scale parameter \( d_g \):

\[
\Pr(y_{gs} = j) = \frac{\exp(d_g \sum_m \sum_k x_{gimk} \beta_{gmk}^S)}{\sum_j \exp(d_g \sum_m \sum_k x_{gimk} \beta_{gmk}^S)} = \frac{\exp(\sum \sum x_{gimk} \beta_{gmk}^S)}{\sum_j \exp(\sum \sum x_{gimk} \beta_{gmk}^S)}
\]

(8)

As before, the scale parameter \( d_g \) is present because two separate data sources are involved in the separate assessment of context-independent and context-dependent dyadic preferences. The term \( \beta_{gmk}^{*S} (= d_g \beta_{gmk}^S) \) is the context dependent dyadic preference adjusted for scale differences.
It is important to recognize that in equations 5 and 7 we separately model attribute-specific influence parameter ($\theta_{gm}$) and dyadic compromise effects ($a_{gm}$). Conceptually it is important to do so: a dyad could arguably select the middle option because it maximizes the influence-weighted utility or because of dyadic compromise effect. In our model specification we allow for each possibility: both DCE ($a_{gm}$) and individual influence ($\theta_{gm}$) are accounted for in the dyadic choice process. The model allows us to uncover dyadic compromise effect after explicitly accounting for member influence. In addition, dyadic compromise effect is modeled after controlling for individual compromise effect as well (equation 6).

Parameter Heterogeneity

The model development so far has focused on a given dyad and the individuals in that dyad. The individual compromise effect is expected to vary across individuals and the dyadic compromise effect also likely varies across dyads. The heterogeneous compromise effect across individuals is captured in Equation (9), while the heterogeneity in the dyadic compromise effect is captured in Equation (10).

(9) \[ \eta_i \sim \text{Normal} \left( \bar{\eta}, B \right) \]

(10) \[ \alpha_g \sim \text{Normal} \left( \bar{\alpha}, D \right) \]

In our dyadic set up in which two members $i_1$ and $i_2$ jointly make a decision to choose a product we assume that each member belongs to a class of individuals with distinct preferences that are identifiable a priori. Examples of such classes in Business-to-Business settings are doctors and nurses. In Business-to-Consumer settings, this could include husbands and wives. Equation 9 is specified separately for each class. To investigate the relationship between the individual
compromise effect and its moderators and that between the dyadic compromise effect and its
moderators, specific elements of $\bar{\eta}$ and $\bar{\alpha}$ could be rewritten as:

\begin{align}
(11) & \quad \bar{\eta} = \Pi z_1 \\
(12) & \quad \bar{\alpha} = \Delta z_2 
\end{align}

where $\Pi$ and $\Delta$ in Equation (11) and (12) are vectors of coefficients that relate the individual and
dyadic compromise effect parameters to a set of observable covariates $z_1$ and $z_2$, respectively. In
addition to characterizing heterogeneity, the proposed model also provides estimates for each
member and the dyad. In the model described above for each dyad the vector of parameters
include individual level preference, compromise effect and scaling parameters ($\beta, \eta, b$) for each
member and dyad level relative influence, compromise effect and scaling parameters ($\theta, \alpha, d$)
level parameters. Heterogeneity distributions for the remaining parameters (preference,
influence, scaling parameters) are also assumed to follow a MVN distribution and details about
model estimation are included in the web appendix.

**SSH Dyadic Compromise Effect Model (Model 2)**

Different from the KNS specification, Sharpe, Staelin and Huber (2008) propose an
alternative model to capture individual compromise effects. Next we build upon the SSH model
to specify an alternative dyadic compromise effect model. The basic model structure for this
model is very similar to the KNS-based model proposed above and we only point to parts that
are different.

In the SSH model the individual context-independent preference $\beta_{imk}$ is obtained as in
equation (1). While the KNS model 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:

\[ \beta_{imk}^S = \beta_{imk} - \gamma_{im} I (k \text{ is the lowest level of attribute } m \text{ in choice set } S) \]
\[ - \phi_{im} I (k \text{ is the highest level of attribute } m \text{ in choice set } S) \]

In the presence of the compromise effect, \( \gamma_{im} \) and \( \phi_{im} \) are expected to be positive. This would be
consistent with the extremeness aversion hypothesis. Conversely, negative \( \gamma_{im} \) and \( \phi_{im} \) 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.

\[ \beta_{imk}^S = \beta_{imk} - \gamma_{im} I (k \text{ is an extreme level of attribute } m \text{ in choice set } S) \]

As before, the term \( \beta_{imk}^{*S} = \beta_{imk} \) is the context dependent preference adjusted for scale
differences and the quantity \( \gamma_{im}^* = b_i \gamma_{im} \) is the scale adjusted compromise effect.

We aggregate the joint preference as before (equation 5 and 6) and the dyadic
compromise effect is captured by \( \tau_{gm} \) as shown below:

\[ \beta_{gmk}^S = \beta_{gmk} - \tau_{gm} I (k \text{ is an extreme level of attribute } m \text{ in choice set } S) \]

The parameter \( \tau_{gm} \) is expected to be positive if the dyadic compromise effect is present. The term
\( \beta_{gmk}^{*S} = \beta_{gmk} \) is the context dependent preference adjusted for scale differences and the
quantity \( \tau_{gm}^* = b_g \tau_{gm} \) is the scale adjusted dyadic compromise effect. Heterogeneity in the
individual and dyadic compromise effects in the SSH model is captured in a manner similar to
equations (9) and (10).
Predictions about the dyadic compromise effect

We indicated earlier that extant literature provides limited guidance on whether the dyadic compromise effect should be present in joint choice settings. On one hand, it could be argued that as a result of group interaction product familiarity increases (Corfman and Kahn 1995), which could lower the group’s proneness to the compromise effect. On the other hand, an argument in favor of the dyadic compromise effect is that groups tend to exaggerate individual biases (Hinsz, Tindale and Nagao 2008). In light of these opposing theoretical arguments about the dyadic compromise effect, we test for its presence empirically.

Unlike the prediction involving the presence or absence of the dyadic compromise effect, the link between individual and dyadic compromise effects is easier to hypothesize. We expect that the higher the individual compromise effect, the higher the dyadic compromise effect. Research has shown that groups are more likely to make reason-based choices than individuals (Barber, Heath and Odean 2003). If group members are concerned about maintaining the approval and respect of their fellow group members, they must find plausible reasons for advocating one alternative over another. If individuals find the intermediate options easiest to choose because it doesn’t force them to make too many difficult tradeoffs they may find it easy to justify such an option to the other group members too. As Lerner and Tetlock (1999) note, “a desire to avoid appearing foolish in front of the audience heightens (a) the need to ensure that one’s choice is securely based on reasons, and thus (b) the preference for options that are easy to justify.” We therefore expect that the higher the tendency that people avoid the extreme options individually, the higher the likelihood that they will choose the intermediate option when making choices as a dyad as well.
In addition to the impact that individual compromise effect may have on dyadic compromise effect, the decision context may also be a factor to consider. In particular, greater number of alternatives in a choice set should enhance the likelihood of dyadic compromise effect. It is well known that an increase in the number of alternatives facing the consumers leads to greater use of simplifying heuristics that eliminate alternatives (e.g., Bettman, Luce and Payne 1998; Johnson and Meyer 1984; Payne 1976). The increased information load associated with greater number of alternatives could cause consumers to eliminate alternatives in order to simplify the processing. The larger the choice set, the greater the likelihood that extreme options are not selected. In dyadic decisions, the processing and integration of the multiple group members’ preferences poses a significant information processing burden and it is therefore likely that dyadic compromise effect increases when the number of alternatives increases.

Next we test our proposed models and investigate how the parameter estimates speak to the predictions outlined above. We begin with a study that helps uncover individual level compromise effect and then extend it to the dyadic context in the second study that follows. The second study involves a national sample of husband-wife dyads that are asked to make financial decisions in order to empirically assess dyadic compromise effects.

**EMPIRICAL APPLICATION**

*Study Flow and Parameter Identification*

Data collection for the two studies we report are visualized in Figure 3. Following Kivetz, Netzer and Srinivasan (2004), part 1 is intended to assess 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—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 1-4 allow us to test for the presence of dyadic compromise effect after accounting for member influence and individual level compromise effects.

**Figure 3: Study Flow**

For each dyad the vector of parameters in the KNS-based model include individual level preference, compromise effect and scaling parameters ($\beta$, $\eta$, $b$) for each member and dyad level.
relative influence, compromise effect and scaling parameters \((\theta, \alpha, d)\) level parameters. The extensive data collected from individuals and the dyads (Figure 3) help identify each one of these parameters. The MCMC chains (see the section on estimation) are very well behaved and converge rapidly. In particular, similar to KNS, part 1 in figure 3 helps identify the parameter \(\beta\) using rating based conjoint data. Using an individual’s choice data, part 2 helps identify the individual compromise effect parameter \((\eta)\) and the scale parameter \((b)\). It may be helpful to recall that the individual compromise effect parameter \((\eta)\) simply allows the \(\beta\) vector to become more concave. The scale parameter \((b)\) rescales the preference vector.

In part 3 we collect ratings based conjoint data from the dyad. Similar to Arora and Allenby (1999), part 3 helps identify the influence parameter \(\theta\). One way to think about the influence parameter is that instead of estimating context independent dyadic preference we use the ratings based data in part 3 to estimate the influence parameter. Conditional on \(\theta\) and \(\beta\), the context independent dyadic preference is still readily available as a function of individual preferences and the influence parameters (equation 5). Finally, analogous to part 1, part 4 helps identify dyadic compromise effect \((\alpha)\) and the scale parameter \((d)\) using each dyad’s choice data. The dyadic compromise effect parameter \((\alpha)\) simply allows the dyad’s context independent preference vector to become more concave. As before, the scale parameter \((d)\) rescales this preference vector.

We report our findings from two studies next. In study 1 we focus our attention on uncovering the individual level compromise effect and rely on parts 1 and 2 in figure 3. Using the same empirical context as in study 1, in study 2 we expand our investigation to a model that tests for dyadic compromise effect in an experimental setting using parts 1-4 in figure 3. In study
2 we test our full model in a dyadic choice setting and investigate how dyadic compromise effect relates to individual compromise effect and how it could be mitigated.

**Study 1**

A total of 276 undergraduate students in a mid-western university participated in this study in exchange for extra credit for a marketing class. We used the laptop computer category in this study and our design focused on three attributes – price, memory and hard drive. The attribute levels were based on the typical values found in the market at the time of data collection (Price: $399 to $999 in increments of $100; Memory: 2GB to 8GB in increments of 1GB; Hard drive: 150GB to 750GB in increments of 100GB). Each respondent was given a ratings based conjoint task (14 profiles; 1-100 scale) and a choice task that involved Pareto-optimal choice sets with seven or five alternatives per set (12 choices). They were also asked questions about their expertise in the computer category, risk aversion and need for uniqueness. Figure A (web appendix) shows an example of the ratings based conjoint exercise which was part 1 of the study.

For part 2 of the study each option of the Pareto-optimal choice sets is described on two attributes (see Figure B, web appendix for an example). For the three attributes, there are three possible combination pairs: \{(Price, Memory); (Price, Hard Drive); (Memory, Hard Drive)\}. For each combination (e.g. memory and price), four choice sets similar to the one shown in Figure B (web appendix) were created. This results in a total of 12 (4 choice sets per combination × 3 combinations) Pareto-optimal choice sets per respondent.
### Table 1: Study 1 Parameter Estimates

<table>
<thead>
<tr>
<th>Preference ($\bar{\beta}$)</th>
<th>Price</th>
<th>Memory</th>
<th>Hard Drive</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>$899$</td>
<td>$2.2$</td>
<td>$6.7$</td>
<td>$250\text{GB}$</td>
<td>$11.5$</td>
</tr>
<tr>
<td>($0.9$)</td>
<td>($1.3$)</td>
<td>($1.2$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$799$</td>
<td>$10.4$</td>
<td>$11.3$</td>
<td>$350\text{GB}$</td>
<td>$15.6$</td>
</tr>
<tr>
<td>($1.1$)</td>
<td>($1.3$)</td>
<td>($1.6$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$699$</td>
<td>$16.0$</td>
<td>$14.9$</td>
<td>$450\text{GB}$</td>
<td>$22.4$</td>
</tr>
<tr>
<td>($1.0$)</td>
<td>($1.1$)</td>
<td>($1.4$)</td>
<td></td>
<td>N/A</td>
</tr>
<tr>
<td>$599$</td>
<td>$22.4$</td>
<td>$20.1$</td>
<td>$550\text{GB}$</td>
<td>$30.5$</td>
</tr>
<tr>
<td>($1.2$)</td>
<td>($1.1$)</td>
<td>($1.5$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$499$</td>
<td>$26.7$</td>
<td>$27.0$</td>
<td>$650\text{GB}$</td>
<td>$35.3$</td>
</tr>
<tr>
<td>($1.3$)</td>
<td>($1.2$)</td>
<td>($1.7$)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$399$</td>
<td>$29.1$</td>
<td>$29.7$</td>
<td>$750\text{GB}$</td>
<td>$39.6$</td>
</tr>
<tr>
<td>($1.3$)</td>
<td>($1.2$)</td>
<td>($1.4$)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Individual Compromise ($\bar{\gamma}$)</th>
<th>SSH Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$26.4$ ($8.8$)</td>
<td>$0.03$ ($0.008$)</td>
</tr>
</tbody>
</table>

The table shows posterior means along with posterior standard deviations in parentheses.

**Results.** We estimated individual level KNS (equations 1-4) and SSH (equations 1, 14, 3 and 4) models using a hierarchical Bayes framework. Based on the deviance information criterion (Gelman et al. 2004) model fit statistics show that the SSH-based model has a better fit than the KNS-based model (DIC=24210 versus 24422). Table 1 reports the posterior mean and standard deviation for the better fitting SSH model. The top portion of the table reports the aggregate context dependent preference for each attribute. As expected, the preference structure for each attribute is monotonic. Importantly, the individual compromise parameter ($\bar{\gamma}$) in the lower portion of the table is positive and significant. This suggests that individuals tend to avoid extremes. Evidence from the KNS model is also consistent with this finding indicating that the result is robust to model specification. Both models uncover the individual compromise effect even when the context independent preference structure is non-linear.
Figure 4 presents the findings for one of the attributes (price) visually. Context independent preference curve ($\bar{\beta}$) illustrates that respondents, on average, have an increasing preference for lower price. Context dependent preference ($\bar{\beta}^*_{\text{c}}$) provides evidence of compromise effect—the lowest and highest price points exhibit significant decline in preference in the choice context. Context dependent preference parameter adjusted for choice ($\bar{\beta}^*_{\text{c}}$) also follows a similar pattern.

**Figure 4: Evidence of Individual Compromise Effect (SSH Model)**

An advantage of the heterogeneous model is that it allows for estimation of the compromise effect at the individual level. We graph the heterogeneity of the individual compromise effect parameter ($\gamma_{im}' = b_i \gamma_{im}$) from the SSH model in Figure 5 (Rossi, Allenby and McCulloch 2005, page 318). The graph shows that most of the subjects are prone to the individual compromise effect, however, some exhibit an extreme seeking tendency ($\gamma_{im}^* < 0$). When we incorporate three moderators (expertise, need for uniqueness and risk aversion) for
individual compromise effects into the model (equation 11), only expertise is found to be significant (prob<.05)\(^2\). This result holds for KNS and SSH models.

**Figure 5: Heterogeneity in Individual Compromise Effect (SSH Model)**

In summary, Study 1 found evidence that on average respondents exhibit the presence of individual level compromise effect (ICE). There is also evidence supporting the heterogeneity in the compromise effect across respondents. The biggest driver of this heterogeneity is lack of expertise. Other factors such as need for uniqueness and risk aversion were not found to be significant drivers of compromise effect in our study. Some individuals were also found to exhibit extreme seeking behavior (Sheng, Parker and Nakamoto 2005).

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\(^2\) We report the Bayesian equivalent of a p-value to indicate statistical significance (Rossi et al. 1996, Arora and Allenby 1999). Using the MCMC estimation procedure, we empirically evaluate the posterior distributions of model parameters to conduct a hypothesis test. For example, to test whether parameter A estimate is greater than B, “prob” simply reports one minus the probability that parameter A exceeds parameter B.
Study 2

As a natural follow up to study 1 where our primary focus was on individual compromise effect, the purpose of study 2 is to test a model that incorporates the dyadic compromise effect. Our primary goals are (1) to test for the presence of the dyadic compromise effect, (2) to uncover factors that may moderate dyadic compromise effect, and (3) to investigate how dyadic compromise effect can be mitigated. In particular we test whether reducing the number of choice options lowers the individual and dyadic compromise effect. We accomplish these goals in a setting that involves husbands and wives and for an important life decision: retirement planning.

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. To qualify the household income had to be above $50,000—we did this assuming that a sizeable retirement investment will likely result in greater task involvement. Each couple was paid $25-$40 for completing the survey3.

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 rest 10 (6%) families. A big majority (79.3% wives and 81.7% husbands) were between 35-55 years old and the couples had

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3 Financial incentives varied by vendor.
an average of 3 kids. The average annual household income was $101,183. Both husbands and wives indicated low expertise on investment matters (husbands’ average=3.20 on a 1-7 scale; wives’ average=2.36) with wives rating themselves lower (p<.05).

Respondents that qualified were contacted to schedule a time in order to conduct the study at their homes. The study was set up such that the respondents could finish it online. To ensure that the respondents pay 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 with them 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 a structure outlined in Figure 3. Each spouse went through 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 ratings task (part 4 and 3, figure 3) for the wife’s account. These two tasks allowed us to assess 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, figure 3) for the husband’s account. As before, these two tasks allowed us to assess member influence and the DCE for the husband’s account. We also measured a variety of individual level variable such as expertise in financial investment, need for uniqueness and risk aversion.

In order to investigate how number of options in the Pareto-optimal choice set impact individual and dyadic compromise effects we included two different set sizes: 5-option (large set size) and 3-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).

In order 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 percent 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 services 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)\(^4\). The Expense Ratio ranged from 0.5% to 1.4%, and was based on the market rates. Figure C (web appendix) provides an example of the ratings based conjoint task used to assess context independent preference.

Like before, for the Pareto-optimal choice sets, each option was described in terms of pairs of attributes. For the three attributes there are three possible pair combinations: \{(Return, Risk); (Return, Expense Ratio); (Risk, Expense Ratio)\}. For each combination, e.g., risk and expense ratio, three 5-option (large set size) and three 3-option choice sets (small set size) were created. There were a total of 18 = 3 (choice sets per combination) × 3 (combinations) × 2 (set size) Pareto-optimal choice sets. Figure D (web appendix) shows an example of a small set size (i.e. 3 options) choice question.

Results. In addition to individual data from each spouse, Study 2 collected joint data on the wife’s account and on the husband’s account. Dyadic SSH-based and KNS-based models (our full models) described earlier were estimated for each.

Table 2: Model Comparison – Husband’s Account (n=148)

<table>
<thead>
<tr>
<th>Model Type</th>
<th>In-Sample Fit</th>
<th>Out-of-Sample Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LMD</td>
<td>DIC</td>
</tr>
<tr>
<td>Model w/o Compromise Effects</td>
<td>-6347</td>
<td>31615</td>
</tr>
<tr>
<td>KNS Model – ICE Only</td>
<td>-6138</td>
<td>30684</td>
</tr>
<tr>
<td>KNS Model – ICE + DCE</td>
<td>-5595</td>
<td>28258</td>
</tr>
<tr>
<td>SSH Model – ICE Only</td>
<td>-5692</td>
<td>25978</td>
</tr>
<tr>
<td>SSH Model – ICE + DCE</td>
<td>-5327</td>
<td>25129</td>
</tr>
</tbody>
</table>

*a: In-sample fit was based on likelihood calculation for 7 choice tasks

*b: Out-of-sample fit was based on prediction calculation for 2 choice tasks

Model fit: Table 2 displays model comparison results for the large set size (5-options) data from husbands’ accounts for both SSH-based and KNS-based models (n=148). Very similar results are found for wives’ accounts as well (n=111). The model fit statistics include deviance information criterion (DIC) and log marginal density (LMD) for in-sample fit and mean absolute deviation (MAD) to measure out-of-sample fit. Focusing our attention on the KNS model, we find that incorporating individual level compromise effects results in better in-sample (LMD= -6138 vs. -6347; DIC=30684 vs.31615) and out-of-sample (MAD=0.293 vs.0.311) fit. Incorporating dyadic compromise effect results in further gains in in-sample (LMD= -5595 vs. -6138; DIC=28258 vs.30684) and out of sample fit (MAD=0.287 vs.0.293). When we compare these results with those for the SSH-based models we find an identical pattern. Further, the SSH-based models have better in-sample and out-of-sample fit for both individual and dyadic models compared to KNS. For example, the SSH-based model accounting for ICE and DCE has a higher LMD (-5327 vs. -5595), lower DIC (25129 vs. 28258) and a lower MAD (0.263 vs. 0.287) than the KNS-based model accounting for ICE and DCE. The overall pattern of results provides
strong evidence supporting the presence of compromise effects at the individual and dyadic level. The SSH based model capturing compromise effects fits the data better than the KNS based model. In the remainder of the paper we report analyses based on the better fitting SSH model.

**Table 3: Preference and Influence Parameter Estimates (Study 2)**

<table>
<thead>
<tr>
<th>Preference (β)</th>
<th>Return Level</th>
<th>Return Wife</th>
<th>Return Husband</th>
<th>Risk Level</th>
<th>Risk Wife</th>
<th>Risk Husband</th>
<th>Expense Ratio Level</th>
<th>Expense Ratio Wife</th>
<th>Expense Ratio Husband</th>
</tr>
</thead>
<tbody>
<tr>
<td>7.36%</td>
<td>11.6 (1.4)</td>
<td>15.3 (1.5)</td>
<td></td>
<td>27% to -10%</td>
<td>9.2 (1.7)</td>
<td>6.3 (1.4)</td>
<td>1.1%</td>
<td>1.6 (1.6)</td>
<td>1.9 (1.2)</td>
</tr>
<tr>
<td>9.02%</td>
<td>19.3 (2.0)</td>
<td>22.3 (2.2)</td>
<td></td>
<td>20% to -4%</td>
<td>19.3 (2.9)</td>
<td>14.6 (2.3)</td>
<td>0.8%</td>
<td>10.8 (1.9)</td>
<td>11.1 (1.9)</td>
</tr>
<tr>
<td>10.13%</td>
<td>19.5 (2.2)</td>
<td>26.8 (2.7)</td>
<td></td>
<td>15% to -1%</td>
<td>19.2 (3.3)</td>
<td>16.9 (2.8)</td>
<td>0.5%</td>
<td>14.8 (2.1)</td>
<td>14.2 (2.0)</td>
</tr>
</tbody>
</table>

| Wife’s Influence on own account | 0.42 (0.08) | 0.38 (0.07) | 0.38 (0.07) |
| Wife’s Influence on Husband’s account | 0.35 (0.05) | 0.35 (0.05) | 0.37 (0.05) |

Note: The table shows posterior means along with posterior standard deviations in parentheses.

**Parameter estimates:** The individual preference and influence estimates for the SSH model are reported in Table 3. The general pattern of preference estimates is reasonable. On average, both husband and wife groups exhibit great sensitivity to each one of the three included attributes and in the predicted direction—there is greater preference for higher return, lower risk and lower expense ratio. Wives on average have significantly less influence (β < 0.5) than the husbands, although they have slightly greater influence on their own accounts than their husbands’. This pattern of results is consistent with a recent survey which reveals that wives are often not as involved in their retirement finances as are their husbands (Fidelity Web, 2011).

Table 4 shows the estimates of individual and joint compromise effects for the large and small set size cases. The top two rows report the individual and joint compromise effect
parameter estimates for the wives’ account; the bottom two rows are those for husbands’ account. For the wives’ account, in the large set size case, the husband and wife on average are prone to the individual compromise effect (wife: 18.8; husband: 10.5; prob<.05) and the dyadic compromise effect (dyad: 17.1; prob<.05). Study 2 therefore provides empirical evidence in support of DCE. Interestingly in the small set size case the magnitude of the individual compromise effect is smaller (wife: 8.9; husband: 4.9; prob<.05). The dyadic compromise effect (dyad: 4.9) in the small set size case is not significantly different from zero.

### Table 4: SSH-based Model Parameter Estimates

**Individual and Joint Compromise Effects**

<table>
<thead>
<tr>
<th></th>
<th>Large set size (5-options)</th>
<th>Small set size (3-options)</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Wife</td>
<td>Husband</td>
<td>Wife</td>
</tr>
<tr>
<td><strong>Wives’ Account</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Compromise Effect</td>
<td>18.8* (3.6)</td>
<td>10.5* (3.0)</td>
<td>8.9* (1.9)</td>
</tr>
<tr>
<td>Joint Compromise Effect</td>
<td>17.1* (5.0)</td>
<td>4.7 (2.9)</td>
<td></td>
</tr>
<tr>
<td><strong>Husbands’ Account</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Compromise Effect</td>
<td>20.8* (4.6)</td>
<td>6.3* (2.6)</td>
<td>8.8* (1.6)</td>
</tr>
<tr>
<td>Joint Compromise Effect</td>
<td>9.1* (4.0)</td>
<td>-2.0 (2.2)</td>
<td></td>
</tr>
</tbody>
</table>

Note: The table shows posterior means along with posterior standard deviations in parentheses. * Indicates significance at the 5% level for individual and joint extreme seeking parameters

The overall pattern of compromise effect results for the husbands’ account (bottom two rows of table 4) is identical to what we found above. The large set size case uncovers significant individual and dyadic compromise effect parameters (wife: 20.8; husband: 6.3; dyad: 9.1; prob<.05). Once again there is empirical evidence in support of DCE. Also, as before, in the small set size case the magnitude of the individual compromise effect is smaller and the dyadic compromise effect is not significantly different from zero. This result further supports the claim that a smaller number of options can reduce both individual and dyadic compromise effects.
We also detect a difference in individual compromise effect by gender in this category. Table 4 indicates that wives on average are more prone to individual compromise effect than husbands for both large as well as small set size cases. For example, for husbands’ account in the large set size case the posterior mean of wives’ individual compromise effect (20.8) is higher than the husbands’ individual compromise effect (6.3). The gender effect is likely driven by wives’ lower expertise in financial investment (wives: mean=2.36 on a 1-7 scale; husbands=3.20). When testing for potential moderators for individual compromise effect—expertise, need for uniqueness and risk aversion—only expertise is found to have a negative and significant effect (prob<.05). This finding is consistent with study 1 where only expertise was found to significantly affect individual compromise effect.

Table 5: Covariate Analysis for Joint Compromise Effect in SSH-Based Model

<table>
<thead>
<tr>
<th></th>
<th>Wives’ Account</th>
<th>Husbands’ Account</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wife’s individual compromise effect</td>
<td>24.1* (13)</td>
<td>9.4 (8.0)</td>
</tr>
<tr>
<td>Husband’s individual compromise effect</td>
<td>6.5 (11)</td>
<td>15.5** (9.2)</td>
</tr>
</tbody>
</table>

Note: The table shows posterior means along with posterior standard deviations in parentheses. * Indicates significance at the 5% level. ** Indicates significance at the 10% level.

We also find that the dyadic compromise effect is smaller for husband’s account compared to wife’s account (e.g. for the small set size case it is 9.1 vs. 17.1). A covariate analysis that links dyadic compromise effect to individual compromise effect (see Table 5) reveals an interesting pattern. For the wives’ account their own individual compromise effect, and not the husbands’, has a significant effect on the dyadic compromise effect (prob<.05). Similarly for the husbands’ account, their own individual compromise effect, and not the wives’, significantly drives the dyadic compromise effect (prob<.10). This finding suggests that individual compromise effect of the person with a greater stake in the choice decision moderates the dyadic compromise effect. Therefore an interesting finding from study 2 is that the individual
level compromise effect of the group member with greater stake is likely to persist as dyadic compromise effect in a joint choice setting.

In summary, in study 2 we found evidence of dyadic compromise effects. The dyadic compromise effect exists in addition to the well-known individual level compromise effect. In our sample wives on average are more prone to the individual compromise effect than husbands, which is likely due to their lower perceived expertise in financial investments. We find evidence that individual compromise effect is associated with dyadic compromise effects. Individual compromise effect of the group member with greater stake in the choice decision appears persist as dyadic compromise effect in a joint choice setting. Choice sets with fewer options could help reduce individual and the joint compromise effect. These findings suggest that informing and educating individuals on financial investments, in particular those with a greater stake in the decision, could help reduce compromise effects and help individuals and dyads make choices that are more closely aligned with their true preference. It is well known that compromise effects could hurt consumer welfare by causing investors to select the intermediate investment options. We find that simpler product offerings with fewer options could help mitigate the potentially deleterious impact of individual and dyadic compromise effects.

**DISCUSSION**

Despite extensive research on the topic, the compromise effect has not been studied in a joint choice setting. When groups make choices (e.g. faculty hiring, committee decisions) it is certainly plausible that the tendency to select the intermediate option maybe at play. In situations that involve multiple decision makers such as family purchases (e.g. an appliance) or organizational buying (e.g. hospital equipment) it is reasonable to ask the question whether individual tendency to select the intermediate option is mitigated or magnified in the joint choice
context. Extant literature does not provide a clear cut answer to this question and the purpose of this paper is to fill this void by investigating compromise effects in a dyadic setting. The general idea of joint compromise effect that we propose applies to larger groups as well, although for empirical convenience it is tested in a dyadic setting in this paper.

We propose a model that captures dyadic compromise effect while controlling for the individual compromise effects and members’ influence in a dyadic choice decision. We identify and examine drivers of individual and dyadic compromise effects. We also propose and test strategies to reduce the individual and dyadic compromise effect that may help individual and dyads select options that are better aligned with their preferences.

What we find

We conducted two studies to test the proposed model and answer our research questions. We find strong evidence to support the presence of dyadic compromise effect. In study 1, we test the individual compromise effect models by Kivetz et al. (2004) and Sharpe et al. (2008) in a heterogeneous setting and assess the moderators of the individual compromise effect. Lack of expertise is found to be a moderator of the individual compromise effect. In Study 2 we examine dyadic compromise effect in a setting in which married couples are asked to make retirement investment choices. We find strong empirical evidence in support of DCE—a model that incorporates DCE provides better fit than a model that does not. We find that greater ICE is associated with greater DCE. Importantly, the ICE tendency of a group member with greater stake in the choice decision appears to result in greater DCE. Because compromise effects result in dyads selecting options not entirely consistent with their true preference, we investigate means to mitigate them. Our findings suggest that choice sets with fewer options help reduce DCE.
Further, education of market segments most vulnerable to compromise effects (e.g. women in the context of retirement planning from our study 2) may be an effective method to mitigate DCE.

**Implications for Financial Planning**

In study 2 we find that women are more prone to the individual compromise effect likely because of their lower perceived expertise level in financial investment. This is troubling because her individual compromise effect will probably be carried over and amplified when she makes investment decision on her account together with her husband. The trends in private pension provisions show that an increasing proportion of pension plans are of the defined contribution type. This type of plan, as 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, not investing according to investors’ true risk preferences could imply significant losses in investor welfare (Brennan and Torous 1999; Bernartzi and Thaler 2001, 2002). Research has shown that women lack financial confidence and are less aware of the investment related topics (Fidelity Web, 2011). Although most plans provide materials and information to participants, including historical performance, projections of future performance, and projections of replacement ratios for particular investment strategies, more education on investment principles and financial planning for retirement is needed especially for women investors. To make it easily accessible to investors with little knowledge, it would help to simplify the information and choices given to them. For example, lifestyle funds and lifecycle funds are good examples of providing investors with well diversified portfolios that are designed to be the main investment in a person’s portfolio.

Lifestyle funds are asset mixes determined by the level of risk and return on the spectrum from the most conservative to the most aggressive growth strategies. Different financial
institutions, though, provide different number of options to the investors. For example, Vanguard and Schwab offer five lifestyle options respectively, while Fidelity has a wider selection of seven. For experts, it is probably a good idea to provide more options since they are better prepared to invest. However, for husband and wife dyads that do not have a lot of expertise in financial investment, it is probably to their advantage to be able to select from a simpler choice set that makes it easier for them to select an option that is more aligned with their true preferences. The simple choice set offered to a dyad could be different for different age groups. For example, Canner et al. (1997) cite a rule of thumb stock allocation percentage of 100 minus age. The small, customized choice set offered to a dyad could be determined by relying on their capacity for risk, such as the “100 minus age” allocation rule thus offering investors freedom of choice without swamping them with “over-choice” that would likely trigger the tendency to select the middle option.

Limitations and Future Research

Rooderkerk, van Heerde and Bijmolt (2011) propose an alternative approach to model the compromise effect. Unlike KNS and SSH that adopt a 2-stage model to uncover compromise effects, RVB uses a 1-stage approach. As shown in this paper, the basic premise of the 2-stage approach is that context independent preference and context dependent preference is assessed separately thus requiring two separate data collection exercises. The 1-stage approach relies on choice data for a single experiment to uncover both preferences and compromise effects. It may be instructive to recast our model relying on the 1-stage approach and test for the presence of ICE and DCE. A methodological challenge in the 1-stage approach is how best to design a choice experiment that can help uncover compromise effect parameter in addition to the preference parameters. The traditional choice designs are constructed to efficiently estimate only
the latter. This presents an interesting design challenge to efficiently estimate model parameters in the Rooderkerk, van Heerde and Bijmolt (2011) model.

In the 2-stage model that we used, the design of the Pareto-optimal choice sets followed existing conventions – the options are characterized on two negatively correlated attributes and are ordered from one extreme to the other (e.g. low price-low quality to high price-high quality). Although such a product assortment presentation is common in the marketplace and consumers tend to simplify their choices by combining correlated quality-related attributes into one meta-quality attribute (Kivetz et al. 2004; Green and Srinivasan 1978; Wright 1975), future research could expand the number of attributes to examine individual and dyadic compromise effects.

Study 2 tested small and large set size options and found that the individual and joint compromise effect are mitigated in when choice sets are smaller. However restricting the number of alternatives to three may not be optimal from the standpoint of consumer welfare. The tradeoff is evident because on one hand an increase in number of alternatives may result in a misalignment of consumers’ true preferences and their choices due to the compromise effects but on the other hand restricting the number of alternatives could lead to a poorer match between preferences and choice offerings and reduce the perceived freedom of choice (e.g., Lancaster 1990; Brehm 1972). It is also well known that consumers may defer a decision when they are faced with larger choice sets (e.g., Iyengar and Lepper 2000). Future research could help determine the optimal number of options in a choice set by more carefully considering these opposing forces as they relate to choice set size.
References


Web Appendix

Figure A: An Example of the Conjoint Exercise in Study 1

In this part of the survey, we are interested in your preference in laptop computers. Suppose you want to buy a laptop computer for yourself.

**Please indicate your likelihood of purchasing each of the laptops on the following scale of 1 to 100.**

<table>
<thead>
<tr>
<th>Extremely Unappealing</th>
<th>Neutral</th>
<th>Extremely Appealing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>50</td>
<td>100</td>
</tr>
</tbody>
</table>

While evaluating these models, remember that a model that is more appealing should be given a higher rating than those that are less appealing. For example, a laptop computer that is very appealing should be given a high number of points (e.g., between 90 to 100). Similarly, a model that is very unappealing should be given a low number of points (e.g., 10 points or less).

<table>
<thead>
<tr>
<th></th>
<th>Price ($)</th>
<th>Memory (GB)</th>
<th>Hard Drive (GB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>599</td>
<td>8</td>
<td>350</td>
</tr>
<tr>
<td>Model 2</td>
<td>999</td>
<td>2</td>
<td>250</td>
</tr>
<tr>
<td>Model 3</td>
<td>499</td>
<td>6</td>
<td>150</td>
</tr>
<tr>
<td>Model 4</td>
<td>799</td>
<td>8</td>
<td>550</td>
</tr>
<tr>
<td>Model 5</td>
<td>799</td>
<td>5</td>
<td>350</td>
</tr>
<tr>
<td>Model 6</td>
<td>699</td>
<td>7</td>
<td>750</td>
</tr>
</tbody>
</table>

Figure B: An Example of the Pareto-Optimal Choice Set in Study 1

Which of the following models do you like best?

Assume that all the models are identical on other dimensions.

<table>
<thead>
<tr>
<th>Memory (GB)</th>
<th>Price ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>2</td>
</tr>
<tr>
<td>Model 2</td>
<td>3</td>
</tr>
<tr>
<td>Model 3</td>
<td>4</td>
</tr>
<tr>
<td>Model 4</td>
<td>5</td>
</tr>
<tr>
<td>Model 5</td>
<td>6</td>
</tr>
<tr>
<td>Model 6</td>
<td>7</td>
</tr>
<tr>
<td>Model 7</td>
<td>8</td>
</tr>
</tbody>
</table>
Web Appendix

Figure C: Study 2 Conjoint Exercise Example

Assume that you can reallocate your family’s entire retirement investment today.

Please indicate the attractiveness of each investment on the following scale of 1 to 100, where 100=extremely appealing and 1=extremely unappealing.

<table>
<thead>
<tr>
<th>Investment</th>
<th>Return</th>
<th>Risk</th>
<th>Expense Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average annual return over the last 20 years</td>
<td>Gain-Loss Swing over the last 20 years</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>10.13%</td>
<td>27% to -10%</td>
<td>0.50%</td>
</tr>
<tr>
<td>2</td>
<td>7.36%</td>
<td>20% to -4%</td>
<td>0.80%</td>
</tr>
<tr>
<td>3</td>
<td>7.36%</td>
<td>27% to -10%</td>
<td>1.40%</td>
</tr>
<tr>
<td>4</td>
<td>5.39%</td>
<td>20% to -4%</td>
<td>1.10%</td>
</tr>
<tr>
<td>5</td>
<td>7.36%</td>
<td>15% to -1%</td>
<td>1.10%</td>
</tr>
</tbody>
</table>

1-100

Investment 1  Investment 2  Investment 3  Investment 4  Investment 5

Figure D: Study 2 Pareto-Optimal Choice Set Question Example

Assume that you can put your family’s entire retirement in one of the following investment today. The investments are similar on the other attributes.

Please choose the investment you prefer most.

<table>
<thead>
<tr>
<th>Investment</th>
<th>Risk</th>
<th>Expense Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gain-Loss Swing over the last 20 years</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>15% to -1%</td>
<td>1.40%</td>
</tr>
<tr>
<td>2</td>
<td>18% to -3%</td>
<td>1.18%</td>
</tr>
<tr>
<td>3</td>
<td>23% to -7%</td>
<td>0.95%</td>
</tr>
</tbody>
</table>

**Risk:** is illustrated by the swing between the largest gain in one year and the largest loss in one year over the last 20 years. Gains have occurred more frequently than losses for all the investments over the last 20 years.

**Expense ratio:** is a measure of what it costs an investment company to operate a mutual fund. Operating expenses are taken out of a fund’s assets and therefore lower the return to a fund’s investors.

☐ Investment 1
☐ Investment 2
☐ Investment 3
Web Appendix  
**Estimation algorithm**

The following Markov chain Monte Carlo algorithm was used to obtain the posterior estimates of the model parameters in SSH-based model. Here we focus on the individual and the joint compromise effect parameters. The parameters in KNS-based models were generated similarly.

1. **Generate \{ \beta_{i1}, i_1=1,...,N \}**.

i_1 and i_2 denote individual members in the dyad and g refers to the dyad. X_{i1} and y_{i1} are the observed data for i_1; X_{i2} and y_{i2} are the observed data for i_2 in Part 1. The full conditional distribution of \beta_{i1} is given by

\[
\begin{align*}
    f(\beta_{i1} | \bar{\beta}_{i1}, D_{i1}, \theta_{gi}, \sigma_{i1}^2, \sigma_{gi}^2) & \\
    \propto \exp \left[ -\frac{1}{2\sigma_{i1}^2} \left( \beta_{i1} - \hat{\beta}_{i1} \right) X_{i1}' X_{i1} \left( \beta_{i1} - \hat{\beta}_{i1} \right) \right] \times \exp \left[ -\frac{1}{2\sigma_{gi}^2} \left( \beta_{i1} - \beta_{i1}' \right) X_{i1}' X_{i1}' \left( \beta_{i1} - \beta_{i1}' \right) \right] \times \exp \left[ -\frac{1}{2}(\beta_{i1} - \bar{\beta}_{i1}) D_{i1}^{-1}(\beta_{i1} - \bar{\beta}_{i1}) \right]
\end{align*}
\]

where

\[
\hat{\beta}_{i1} = (X_{i1}' X_{i1})^{-1} X_{i1}' u_{i1}
\]

\[
\beta_{i1}' = (X_{i1}' X_{i1}')^{-1} X_{i1}' u_{i1}', \quad X_{i1}' = X_{i1} \theta_{gi} \quad \text{and} \quad u_{i1}' = u_{gi} - \sum_{k} X_{i1} \beta_{i1,k} (1 - \theta_{gi})
\]

Therefore,

\[
f(\beta_{i1} | \bar{\beta}_{i1}, D_{i1}, \theta_{gi}, \sigma_{i1}^2, \sigma_{gi}^2) \sim N(\tilde{\beta}_{i1}, V_{i1})
\]

where

\[
V_{i1} = \left[ \sigma_{i1}^{-2} (X_{i1}' X_{i1}) + \sigma_{gi}^{-2} (X_{i1}' X_{i1}') + D_{i1}^{-1} \right]^{-1}
\]

\[
\tilde{\beta}_{i1} = V_{i1} \left[ \sigma_{i1}^{-2} (X_{i1}' y_{i1}) + \sigma_{gi}^{-2} (X_{i1}' y_{i1}') + D_{i1}^{-1} \beta_{i1} \right]
\]

2. **Generate \{ \bar{\beta}_{i1}, i_1=1,...,N \}**

\[
\begin{align*}
    f(\bar{\beta}_{i1} | \{ \beta_{i1} \}, D_{i1}) & \propto f(\{ \beta_{i1} \} | \bar{\beta}_{i1}, D_{i1}) \times f(\bar{\beta}_{i1}) \\
    \propto \exp \left[ -\frac{1}{2}(\beta_{i1} - \bar{\beta}_{i1}) D_{i1}^{-1}(\beta_{i1} - \bar{\beta}_{i1}) \right] \times \exp \left[ -\frac{1}{2}(\bar{\beta}_{i1} - \zeta) A^{-1} (\bar{\beta}_{i1} - \zeta) \right] \\
    \sim MVN \left( N D_{i1}^{-1} + A^{-1} \right)^{-1} \left( \sum_{i=1}^{N} D_{i1}^{-1} \beta_{i1} + A^{-1} \zeta \right) \left( N D_{i1}^{-1} + A^{-1} \right)^{-1}
\end{align*}
\]
where the prior distribution of $\beta_i$ is assumed to be multivariate Normal with mean $\zeta$ and covariance matrix $A$. In this estimation, we use a diffuse prior, where $\zeta=0$ and $A=100I$.

3. Generate $D_{i1}$

$$f(D_i \mid \beta_i, \overline{\beta}_i) \sim \text{Inverted Wishart}(D_0 + N, D_0 + \Sigma_h (\beta_h - \overline{\beta}_h) (\beta_h - \overline{\beta}_h))$$

The prior distribution of $D_{i1}$ is assumed to be Inverted Wishart ($d_0, D_0$). In this estimation, we set $d_0 = 1 + \text{length of vector } \beta_i$, and $D_0 = I$.

4. Generate $\sigma_i^2$

$$f(\sigma_i^2 \mid \beta_i) \sim \text{Gamma} \left( g + T_i / 2, G + \sum_i (u_i - x_i \beta_i) (u_i - x_i \beta_i) / 2 \right)$$

where $g$ and $G$ are the prior degrees of freedom and precision, respectively. In the estimation, we used $g = G = 2$.

5. Generate $\{\beta_i, i=1,...,N \}, \overline{\beta}_i, D_{i2}, \sigma_i^2$

Follow the same steps as in 1-4.

6. Generate $\{\gamma_i=(y_{i1}, y_{i2}), i=1,...,N; i=1,...,N \}$

For a given individual $i$, $S$ denotes the Pareto-optimal choice sets. The full conditional distribution of $\gamma_i$ is given by

$$f(\gamma_i \mid \beta_i, \overline{\beta}_i, \gamma, \Omega, b_i, S, y_{ia})$$

$$\propto f(\gamma_i \mid \Omega) \times \text{Pr}(y_{ia} \mid \gamma_i, \beta_i, b_i, S)$$

$$\propto \exp \left[ -1/2 (\gamma_i - \overline{\gamma}) \Omega^{-1} (\gamma_i - \overline{\gamma}) \right] \times \text{Pr}(y_{ia} \mid \gamma_i, \beta_i, \beta_{i1}, b_i, S)$$

where $\text{Pr}(y_{ia})$ is obtained through Equation (4). A random-walk Metropolis-Hastings step is used to generate $\gamma_i$ separately for each respondent. Let $\gamma_i^* = \gamma_i + s \times N(0, I)$ represent the proposed candidate new draw, and let $\gamma_i$ represent the current draw. Accept $\gamma_i^*$ with

$$\text{probability} = \min \left( \frac{\exp \left[ -1/2 (\gamma_i^* - \overline{\gamma}) \Omega^{-1} (\gamma_i^* - \overline{\gamma}) \right]}{\exp \left[ -1/2 (\gamma_i - \overline{\gamma}) \Omega^{-1} (\gamma_i - \overline{\gamma}) \right]}, 1 \right)$$

7. Generate $\overline{\gamma}$ from a multivariate Normal (MVN) distribution as

$$f(\overline{\gamma} \mid \gamma_i, \Omega) \propto f(\gamma_i \mid \overline{\gamma}, \Omega) \times f(\overline{\gamma})$$

$$\propto \exp \left[ -1/2 (\gamma_i - \overline{\gamma}) \Omega^{-1} (\gamma_i - \overline{\gamma}) \right] \times \exp \left[ -1/2 (\overline{\gamma} - \zeta) A^{-1} (\overline{\gamma} - \zeta) \right]$$

$$\sim \text{MVN} \left( N \Omega^{-1} A^{-1} \left( \sum_{i=1}^{N} \Omega_i^{-1} \gamma_i + A^{-1} \zeta \right), (N \Omega^{-1} A^{-1})^{-1} \right)$$

where the prior distribution of $\overline{\gamma}$ is assumed to be multivariate Normal with mean $\zeta$ and covariance matrix $A$. In this estimation, we use a diffuse prior, where $\zeta=0$ and $A=100I$.

8. Generate $\Omega$ from an Inverted Wishart distribution as
The prior distribution of $\Omega$ is assumed to be Inverted Wishart ($d_0, D_0$). In the estimation, we set $d_0=1+$ the length of vector $\gamma$, and $D_0=I$.

9. **Let the scale parameter** $b_i=\exp(t_i)$. **Generate** \{t_i=(t_{i_1}, t_{i_2}), i=1,..,N; i_2=1,..,N \}

For a given individual $i$, the full conditional distribution of $t_i$ is given by

$$f(t_i \mid \gamma, \beta_{_0}, \beta_{_1}, \tilde{t}, P, S, y_o) \propto f(t_i \mid \tilde{t}, P) \times \text{Pr}(y_{is} \mid \gamma, \beta_{_0}, \beta_{_1}, b_i, S)$$

$$\propto \exp\left[-1/2(t_i - \tilde{t})^\top P^{-1}(t_i - \tilde{t})\right] \times \text{Pr}(y_{is} \mid \gamma, \beta_{_0}, \beta_{_1}, t_i, S)$$

where $\text{Pr}(y_{is})$ is obtained through Equation (4). A random-walk Metropolis-Hastings step is used to generate $t_i$ separately for each respondent. Let $t_i^* = t_i + s \times N(0, I)$ represent the proposed candidate new draw, and let $t_i$ represent the current draw. Accept $t_i^*$ with

$$\text{probability} = \min\left(\frac{\exp\left[-1/2(t_i^* - \tilde{t})^\top \Omega^{-1}(t_i^* - \tilde{t})\right]}{\exp\left[-1/2(t_i - \tilde{t})^\top \Omega^{-1}(t_i - \tilde{t})\right]}, 1\right)$$

10. **Generate $\tilde{\epsilon}$ from a multivariate Normal (MVN) distribution as**

$$f(\tilde{\epsilon} \mid t_i, \tilde{t}, P) \propto f(t_i \mid \tilde{t}, P) \times f(\tilde{t})$$

$$\propto \exp\left[-\sum_{i=1}^{N}\left[1/2(t_i - \tilde{t})^\top P^{-1}(t_i - \tilde{t})\right]\right] \times \exp\left[-1/2(\tilde{t} - \zeta)^\top A^{-1}(\tilde{t} - \zeta)\right]$$

$$\sim \text{MVN}\left((NP^{-1} + A^{-1})^{-1}, \left(\sum_{i=1}^{N}P^{-1}t_i + A^{-1}\zeta\right), (NP^{-1} + A^{-1})^{-1}\right)$$

where the prior distribution of $\tilde{\epsilon}$ is assumed to be multivariate Normal with mean $\zeta$ and covariance matrix $A$. In this estimation, we use a diffuse prior, where $\zeta=0$ and $A=100I$.

11. **Generate $P$ from an Inverted Wishart distribution as**

$$f(P \mid t_i, \tilde{t}) \sim \text{Inverted Wishart}\left(N + d_o, \sum_{i=1}^{N}(t_i - \tilde{t})^\top(t_i - \tilde{t}) + D_0\right)$$

The prior distribution of $P$ is assumed to be Inverted Wishart ($d_o, D_0$). In the estimation, we set $d_o=1+$ the length of vector $t_i$, and $D_0=I$.

12. **Generate $\theta_g$.**

The full conditional distribution of $\theta_g$ is

$$f(\theta_g \mid \tilde{\theta}_g, W, \beta_{_0}, \beta_{_1}, \sigma^2_g) \sim N(\tilde{\theta}_g, F)$$

where

$$F = \left[W_g^{-1} + \sigma^2_g(u^* u^*)\right]^{-1}$$
\[
\tilde{\theta}_g = F \left[ W_g^{-1} \tilde{\theta}_g + \sigma_g^{-2} (u^* u^*) \tilde{\theta}_g \right]^{-1}
\]
\[
u_{gmk}^* = x_{gmk} (\beta_{i,mk} - \beta_{i,mk})\]
\[
\hat{\beta}_g = (u^* u^*)^{-1} u^* y^* \quad \text{and} \quad y_g^* = u_g - x_g \beta_i,
\]

13. Generate \{\tilde{\theta}_g, g=1,\ldots,N\}

\[
f(\tilde{\theta}_g | \{\theta_g\}, Z_g) \propto f(\{\theta_g\} | \tilde{\theta}_g, Z_g) \times f(\tilde{\theta}_g)
\]
\[
\propto \exp \sum_{g=1}^{N} \left[ -1/2 (\theta_g - \tilde{\theta}_g) Z_g^{-1} (\theta_g - \tilde{\theta}_g) \right] \times \exp \left[ -1/2 (\tilde{\theta}_g - \varsigma) A^{-1} (\tilde{\theta}_g - \varsigma) \right]
\]
\[
\sim MVN \left( (NZ_g^{-1} + A^{-1})^{-1} \left( \sum_{g=1}^{N} Z_g^{-1} \theta_g + A^{-1} \varsigma \right), (NZ_g^{-1} + A^{-1})^{-1} \right)
\]

where the prior distribution of \(\tilde{\theta}_g\) is assumed to be multivariate Normal with mean \(\varsigma\) and covariance matrix \(A\). In this estimation, we use a diffuse prior, where \(\varsigma=0\) and \(A=100I\).

14. Generate \(W_g\)

\[
f(W_g | \{\theta_g\}, \tilde{\theta}_g) \sim \text{Inverted Wishart} \left( d_0 + N, D_0 + \sum_g (\theta_g - \tilde{\theta}_g) (\theta_g - \tilde{\theta}_g) \right)
\]

The prior distribution of \(W_g\) is assumed to be Inverted Wishart \((d_0, D_0)\). In the estimation, we set \(d_0=1+\) the length of vector \(\theta_g\), and \(D_0=I\).

15. Generate \{\tau_g, g=1,\ldots,N\}

For a given couple \(\varphi\), the full conditional distribution of \(\tau_g\) is given by

\[
f(\tau_g | \varphi, \theta_g, \beta_i, \beta_{i_2}, \tilde{\tau}, K, b_i, d_g, S, y_{gs})
\]
\[
\propto f(\tau_g | \tilde{\tau}, K) \times \text{Pr}(y_{gs} | \varphi, \theta_g, \beta_i, \beta_{i_2}, b_i, d_g, S)
\]
\[
\propto \exp \left[ -1/2 (\tau_g - \tilde{\tau}) K^{-1} (\tau_g - \tilde{\tau}) \right] \times \text{Pr}(y_{gs} | \varphi, \theta_g, \beta_i, \beta_{i_2}, b_i, d_g, S)
\]

where \(\text{Pr}(y_{gs})\) is obtained through Equation (7). A random-walk Metropolis-Hastings step is used to generate \(\tau_g\) separately for each respondent. Let \(\tau_g^* = \tau_g + s \times N(0, I)\) represent the proposed candidate new draw, and let \(\tau_g\) represent the current draw. Accept \(\tau_g^*\) with

\[
\text{probability} = \min \left( \frac{\exp \left[ -1/2 (\tau_g^* - \tilde{\tau}) K^{-1} (\tau_g^* - \tilde{\tau}) \right]}{\exp \left[ -1/2 (\tau_g - \tilde{\tau}) K^{-1} (\tau_g - \tilde{\tau}) \right]} , 1 \right)
\]

16. Generate \(\tilde{\tau}\) from a multivariate Normal (MVN) distribution as

\[
f(\tilde{\tau} | \{\tau_g\} , K) \propto \prod_{g=1}^{N} f(\tau_h | \tilde{\tau}, K) \times f(\tilde{\tau})
\]
\[
\propto \exp \sum_{g=1}^{N} \left[ -1/2 (\tau_h - \tilde{\tau}) K^{-1} (\tau_h - \tilde{\tau}) \right] \times \exp \left[ -1/2 (\tilde{\tau} - \varsigma) A^{-1} (\tilde{\tau} - \varsigma) \right]
\]
\[
\sim MVN \left( (NK^{-1} + A^{-1})^{-1} \left( \sum_{g=1}^{N} K^{-1} \tau_h + A^{-1} \varsigma \right), (NK^{-1} + A^{-1})^{-1} \right)
\]
where the prior distribution of \( \tau \) is assumed to be multivariate Normal with mean \( \zeta \) and covariance matrix \( A \). In this estimation, we use a diffuse prior, where \( \zeta=0 \) and \( A=100I \).

### 17. Generate \( K \) from an Inverted Wishart distribution as

\[
f(K \mid \{\tau_g\}, \bar{\tau}) \sim \text{Inverted Wishart} \left( N + d_0, \sum_{g=1}^{N} (\tau_g - \bar{\tau}) (\tau_g - \bar{\tau}) + D_0 \right)
\]

The prior distribution of \( K \) is assumed to be Inverted Wishart \((d_0, D_0)\). In the estimation, we set \( d_0=1+ \) the length of vector \( \tau_g \), and \( D_0=I \).

### 18. Let the scale parameter \( d_g=\exp(q_g) \). Generate \( \{q_g, g=1,...,N\} \)

For a given couple \( g \), the full conditional distribution of \( q_g \) is given by

\[
f(q_g \mid \tau_g, \gamma_i, \theta_g, \beta_i, \beta_i, \bar{\tau}, q, M, b_i, S, y_{gs})
\]

\[
\propto f(q_g \mid \bar{q}, M) \times \text{Pr}(y_{gs} \mid \gamma_i, \theta_g, \beta_i, \beta_i, b_i, q_g, S)
\]

\[
\propto \exp\left[ -1/2 (q_g - \bar{q}) M^{-1} (q_g - \bar{q}) \right] \times \text{Pr}(y_{gs} \mid \gamma_i, \theta_g, \beta_i, \beta_i, b_i, q_g, S)
\]

A random-walk Metropolis-Hastings step is used to generate \( q_g \) separately for each respondent. Let \( q_g^* = q_g + s \times N(0, I) \) represent the proposed candidate new draw, and let \( \tau_g \) represent the current draw. Accept \( q_g^* \) with probability \[ \min \left( \frac{\exp\left[ -1/2 (q_g^* - \bar{q}) K^{-1} (q_g^* - \bar{q}) \right]}{\exp\left[ -1/2 (q_g - \bar{q}) K^{-1} (q_g - \bar{q}) \right]} \right) \]

### 19. Generate \( \bar{q} \) from a multivariate Normal (MVN) distribution as

\[
f(\bar{q} \mid \{q_g\}, \Lambda) \propto f(q_g \mid \bar{q}, \Lambda) \times f(\bar{q})
\]

\[
\propto \exp \sum_{g=1}^{N} \left[ -1/2 (q_g - \bar{q}) \Lambda^{-1} (q_g - \bar{q}) \right] \times \exp \left[ -1/2 (\bar{q} - \zeta) A^{-1} (\bar{q} - \zeta) \right]
\]

\[
\sim \text{MVN} \left( N \Lambda^{-1} + A^{-1} \right)^{-1} \left( \sum_{g=1}^{N} \Lambda^{-1} q_g + A^{-1} \zeta \right), (N \Lambda^{-1} + A^{-1})^{-1}
\]

where the prior distribution of \( \bar{q} \) is assumed to be multivariate Normal with mean \( \zeta \) and covariance matrix \( A \). In this estimation, we use a diffuse prior, where \( \zeta=0 \) and \( A=100I \).

### 20. Generate \( \Lambda \) from an Inverted Wishart distribution as

\[
f(\Lambda \mid \{q_g\}, \bar{q}) \sim \text{Inverted Wishart} \left( N + d_0, \sum_{g=1}^{N} (q_g - \bar{q}) (q_g - \bar{q}) + D_0 \right)
\]

The prior distribution of \( \Lambda \) is assumed to be Inverted Wishart \((d_0, D_0)\). In the estimation, we set \( d_0=1+ \) the length of vector \( q_g \), and \( D_0=I \).