Future Preference Uncertainty and Diversification: The Role of Temporal Stochastic Inflation

LINDA COURT SALISBURY
FRED M. FEINBERG*

Consumers’ choices tend to display greater variety when made for future versus immediate consumption. Previous accounts of such diversification differences suggested that they are driven primarily by (deterministic) shifts in underlying preference. Through a series of simulation studies, we propose and assess an alternative contributory mechanism: temporal stochastic inflation, the greater uncertainty typifying choices made for the future. We find effect sizes to be strongly influenced by relative brand attractiveness, brand attractiveness uncertainty, and degree of stochastic inflation, although not preference heterogeneity. Moreover, effect sizes are consistent with prior studies that attributed diversification differences to underlying preference shifts alone.

Consumers’ choices are typically made for consumption in the future. We rarely dine at the grocery store or select our vacation on a whim at the airport. Given the frequency and ubiquity of such decisions, one would imagine choices made for future consumption would tend to match up well with those made at the time of consumption itself. Yet this is not always so. Simonson (1990) first demonstrated that consumers, making repeated choices from an assortment, tend to choose greater variety and select their favorite options less often, when their choices are made now for future consumption, rather than later, at the time of consumption. This phenomenon is robust, has been replicated by Read and Loewenstein (1995), and was verified for hedonic and risky choices (Read et al. 2001; Read, Loewenstein, and Kalyanaraman 1999), packaged goods (Simonson and Winer 1992), as well as for shorter interconsumption time periods (Read et al. 2001). Marketers sometimes highlight this tendency explicitly, as in the classic advertising jingle, “Sometimes you feel like a nut, sometimes you don’t.”

Prior research approaches have presumed, usually tacitly, that differences in observed behavioral outcomes—consumers’ choices—are driven by (differences in) deterministic, rather than stochastic, elements (Read and Loewenstein 1995; Simonson 1990; Simonson and Winer 1992; Walsh 1995). That is, decomposing consumer utility in the typical manner as \( U = V + \epsilon \), previous investigations have focused on \( V \), the deterministic component, as opposed to \( \epsilon \), the stochastic component, of utility. Our analysis will examine the appropriateness of this assumption and study the interrelationships among consumption time delay, patterns across and uncertainties among preferences, and resulting choices.

Building on Simonson’s (1990) proposal that choosing for the future increases consumers’ uncertainty about future preferences, we examine whether greater preference uncertainty (and subsequent diversification) when choosing for future consumption can arise not only from anticipating changes in underlying tastes (which, as explained subsequently, can be represented by the mean or deterministic portion of utility) but also from increased uncertainty about precisely how enjoyable each available item will appear at time of consumption (which can be captured by the stochastic portion of utility). In other words, we allow for the possibility that the consumer expects the relative ordering of underlying tastes to be stable over time (Loewenstein and Angner 2003), but the stochastic “noise” around the mean attractiveness of each item may become inflated when choosing for the future, thereby increasing preference uncertainty. Varying degrees of stochasticity can influence pre-

*Linda Court Salisbury (salisbli@bc.edu) is assistant professor of marketing at the Carroll School of Management, Boston College, 140 Commonwealth Avenue, Chestnut Hill, MA 02167. Fred M. Feinberg (feinf@umich.edu) is Hallman Fellow and professor of marketing, Stephen M. Ross School of Business, University of Michigan, 701 Tappan Street, Ann Arbor, MI 48109. This article is based on the first author’s dissertation at the Stephen M. Ross School of Business, University of Michigan. The authors thank Christie Brown, Norbert Schwarz, Frank Yates, the reviewers, the associate editor, and editor for their valuable comments.

John Deighton served as editor and Stephen Nowlis served as associate editor for this article.

Electronically published March 24, 2008
The process of choosing an item now for future consumption presumably involves some estimation of one’s anticipated utility for the item (March 1978). However, consumers often have difficulty predicting future utility (Kahneman and Snell 1992; Kahneman, Wakker, and Sarin 1997); time delay, specifically, can lead to greater uncertainty and thereby influence choice (Keren and Roelofsz 1995). We can examine such effects, both analytically and graphically, if temporal distance between choice and consumption increases uncertainty (represented by stochastic variation) when choosing for the future. Figure 1 contrasts the variance of utility values when choosing for immediate (IMM) versus for future (FUT) consumption via a “stochastic variance scaling factor,” $\sigma_{J} \geq 1$, where $U_i = V_i + \sigma_i \epsilon_i$ and $\sigma_{FUT} > \sigma_{IMM}$.

The Effect of Temporal Stochastic Inflation on Choice Probability

Figure 1 illustrates the framework we explore throughout the article, but for a single dichotomous choice, thus enabling a graphical examination of how diversification differences arise. Each panel in figure 1 compares utility distributions for two hypothetical alternatives, A and B, among which a consumer chooses. The mean of each utility distribution represents the consumer’s mean liking for, or predisposition toward, the alternative (Simonson 1990); the dis-
FUTURE UNCERTAINTY AND DIVERSIFICATION

Distribution around the mean characterizes the stochastic noise in perceived attractiveness. The leftward graphs depict choosing an item now to consume immediately; the rightward graphs depict choosing an item now to consume in some future time period. The far right of each panel compares the probability of choosing option \( B \) (the more favored option) in each temporal condition numerically, to supplement and clarify the graphical illustration. Formally, this probability is given by (where \( t = 1 \) for IMM and \( t > 1 \) for FUT):

\[
P_B = \Pr(e_{At} - e_{Bt} < \frac{V_B - V_A}{\sigma_i}).
\]  

(1)

Note that, throughout figure 1, because alternative \( B \) has greater mean (i.e., deterministic) utility than alternative \( A \) (\( V_B > V_A \)), it will always have greater choice probability, so long as the error distribution is identical. (Note that we do not wish to impose the assumption that the stochastic component of utility be symmetric or have zero mean; indeed, for logit-type models—on which our simulations will be built—neither holds. “Mean” should be taken as shorthand for the nonstochastic, deterministic portion of utility, as distinguished from utility variance.) However, if uncertainty (stochastic variance) is greater when choosing for the future (\( \sigma_{FUT} > \sigma_{IMM} \)), the probability that the utility of \( A \) will be larger than that of \( B \) increases as well; that is, \( P(U_{FUT} > U_{FUT}) > P(U_{IMM} > U_{IMM}) \). This can be verified informally by eyeballing the overlap in the utility curves for options \( A \) and \( B \) within any of the four panels of figure 1 and formally via equation 1.

Consequently, the less favored alternative \( (A) \) is more likely to be chosen for future, rather than for immediate, consumption and vice versa for the more favored alternative \( (B) \). This can, in fact, be demonstrated rigorously for any number of items: when the ratio of the stochastic variation (\( \sigma_{FUT}/\sigma_{IMM} \)) between two choice situations is greater than one (as per fig. 1A), the most favored (highest \( V_i \); here, \( V_B \)) item is less likely, and the least favored (lowest \( V_i \); here, \( V_A \)) item is more likely; to be chosen; moreover, these are the only such general directional predictions stemming from a random utility framework (proof available from the authors).

Correspondingly, testable predictions about diversification concern choice probabilities for individuals’ most and least favored options. Thus, as did prior researchers (Read et al. 2001; Read and Loewenstein 1995; Simonson 1990; Walsh 1995), we concern ourselves with the following questions: to what extent do consumers stray from choosing their most favored option, and which conditions most strongly predispose them to do so? An analogous examination for the least favored option can be readily conducted; however, choices of least favored items (in larger choice sets) are so rare as to make this a poor choice of dependent measure. Accordingly, we henceforth use the term “diversification” to refer to the probability of a consumer’s choosing an option other than his or her most favored item. “Diversification difference” therefore corresponds to the degree to which a consumer is more likely to choose a nonfavorite option for the future versus for now; in our simple dichotomous example, this is \( P_{B,FUT} - P_{B,IMM} \). Because we subsequently consider more than two items, we calculate diversification difference using the more convenient, equivalent expression \( P_{diff} = P_{B,IMM} - P_{B,FUT} \), where \( B \) is the individual’s most favored item.

Preference Uncertainty and Diversification Differences

We next examine the sensitivity of \( P_{diff} \) to three quantities that influence preference uncertainty, and thereby both choice probabilities and subsequent diversification: the temporal inflation factor, \( \sigma_{FUT}/\sigma_{IMM} \); the difference in mean attractiveness of available options, \( V_{diff} = V_B - V_A \); and immediate uncertainty about item attractiveness, \( \sigma_{IMM} \). These are illustrated via figure 1B, C, and D, respectively, where each panel compares IMM to FUT and provides an illustrative (hypothetical) numerical example isolating the effect of a particular focal quantity on \( P_{diff} \) for a one-time, dichotomous choice. Let us consider each in turn.

Effect of Altering the Temporal Stochastic Inflation Factor, \( \sigma_{FUT}/\sigma_{IMM} \). We previously saw that \( P_{diff} \) is positive when the inflation factor (\( \sigma_{FUT}/\sigma_{IMM} \)) is greater than one and that \( P_{B} \) decreases in \( \sigma_i \) from equation 1. Figure 1A and B depict the effects of increasing the inflation factor, causing ever greater overlap of the utility distributions for the two items when choosing for the future: the probability of choosing the more favored item (\( B \)) decreases to an even greater degree than in the “base” case (fig. 1A), thereby increasing diversification differences. This effect is also apparent in the numerical example, where \( P_{diff} \) increases from 0.122 to 0.167 when \( \sigma_{FUT}/\sigma_{IMM} \) increases from two to three.

Effect of Altering Relative Item Attractiveness, \( V_{diff} \). Preference uncertainty, and therefore choice probabilities, are influenced by the relative attractiveness (i.e., differences in mean utilities) of available alternatives (Anderson 2003; Dhar 1997; Ratner and Kahn 2001). Referring to figure 1 and/or equation 1, as the difference in means (\( V_{diff} \)) decreases, the probability of choosing alternative \( B \) (\( P_{B} \)) decreases as well, but \( P_{B} \) can decrease to a lesser degree when choosing for later versus for now, because \( \sigma_{FUT} > \sigma_{IMM} \). The net result is that diversification difference (\( P_{diff} = P_{B,IMM} - P_{B,FUT} \)) tends to decrease as mean attractiveness difference (\( V_{diff} \)) gets smaller. In simpler terms, we expect consumers to diversify their choices more, regardless of time delay, as alternatives become closer in mean attractiveness. At the extreme, such as a chocolate lover choosing between two different Godiva morsels, diversification differences would likely be small. Figure 1A and C illustrate this point graphically; in the numerical example, \( P_{diff} \) decreases from 0.122 to 0.068 as \( V_{diff} \) decreases from 1.0 to 0.5 (holding constant \( \sigma_{IMM} = 1 \) and \( \sigma_{FUT}/\sigma_{IMM} = 2 \) ).
Effect of Altering Immediate Attractiveness Uncertainty, $\sigma_{\text{IMM}}$. Consumers experience uncertainty about item attractiveness, whether choosing for immediate consumption ($\sigma_{\text{IMM}}$) or for future consumption ($\sigma_{\text{FUT}}$), and it is well known that outcome uncertainty affects diversification behavior (Fox, Ratner, and Lieb 2005; Rubinstein 2002). Figure 1D illustrates the effects of increasing the degree of immediate uncertainty ($\sigma_{\text{IMM}}$), while holding degree of temporal inflation ($\sigma_{\text{FUT}}/\sigma_{\text{IMM}}$) constant: the utility curves for both options spread out, forcing their choice probabilities closer, whether choosing for now or for the future. Consequently, the more favored option (B) is less likely to be chosen, and diversification differences ($P_{\text{diff}}$) tend to decrease as $\sigma_{\text{IMM}}$ increases. Comparing figure 1A and D illustrates this result; numerically, $P_{\text{diff}}$ decreases from 0.122 to 0.088 as $\sigma_{\text{IMM}}$ increases from 1.0 to 1.5.

Effects for Extreme Values of $V_{\text{diff}}$ and $\sigma_{\text{IMM}}$. We note that these directional tendencies are literally just that: examples can be devised where the effects of changing either $V_{\text{diff}}$ or $\sigma_{\text{IMM}}$ are opposite in sign to those illustrated. Both of these effects are, in fact, U-shaped, but any such directional reversals occur for values well outside typical ranges (as will be seen in study 1 below). For example, when $V_{\text{diff}}$ is exceedingly large (e.g., greater than two; see fig. 1), increasing $\sigma_{\text{IMM}}$ can cause diversification differences ($P_{\text{diff}}$) to increase. Because such effects occur only for extreme values of the focal quantities, we will not explore them systematically but will note them when they occur in our subsequent simulation studies.

In summary, temporal stochastic inflation is predicted to increase the probability of choosing one’s most favored alternative, leading to differences in diversification for immediate versus future consumption. The magnitude of diversification differences ($P_{\text{diff}}$) will tend to be smaller when temporal stochastic inflation ($\sigma_{\text{FUT}}/\sigma_{\text{IMM}}$) lessens, when mean utility differences ($V_{\text{diff}}$) decrease, or when immediate uncertainty ($\sigma_{\text{IMM}}$) increases. We note that these three effects can operate alone or in concert to affect the degree of diversification; we will explore such interactions as they arise in our simulations.

We next present a set of simulation studies to test these predictions for multiple items, sequences of choices, and other “real world” elements such as consumer heterogeneity and correlated brand preferences. Each study manipulates a set of input parameters to test their effects on the probability of choosing the most favored alternative in a choice set. Throughout, we focus on effect sizes: how strongly each input parameter affects the magnitude of diversification differences. We examine the range of possible effect sizes both in theory (study 1) and using both real preference data and measured coefficient values (study 2).

**METHODOLOGY**

Distinguishing the effects of the deterministic and stochastic components of utility requires an approach that can assess their consequent effects on choice. One possibility involves conducting a field or laboratory experiment and econometrically assessing effects on actual consumer choices. While this approach offers some degree of face validity, it is nonetheless rife with potential measurement errors and confounds among our three key constructs—temporal stochastic inflation, mean attractiveness differences, and immediate uncertainty. Simulation, by contrast, ensures that differences in summary measures arise solely from manipulated quantities and not from missing or mismeasured covariates, unobserved heterogeneity, environmental factors, nonlinearity, or various model misspecifications.

We thus carry out our investigation via a sequence of two Monte Carlo simulation studies. Study 1 examines the three variables analyzed previously for dichotomous choice; consumers’ preferences are taken to be homogeneous, so that no individual-specific favorites need be accounted for. Study 2 introduces preference heterogeneity and real preference distributions from newly collected data, coupled with decision parameter values based on analogous coefficient estimates from prior literature. Thus, although coefficients (i.e., effects strengths) are not assessed econometrically, study 2 incorporates them to the extent reported in prior research that did. Orthogonalizing the simulation designs allows us to isolate the effects of temporal stochastic inflation; we can then assess whether induced diversification differences compare in magnitude to those reported in prior literature, over a range of values for other, independently manipulated quantities (i.e., $V_{\text{diff}}$ and $\sigma_{\text{IMM}}$).

**Simulated Decision Task**

We define our simulated choice task consistent with previous research (Read and Loewenstein 1995; Simonson 1990) to facilitate comparisons, as well as to add realism to study 2, as described below. Simonson (1990, experiment 2) and Read and Loewenstein (1995, experiment 1) had participants choose three snacks from a set of six to be consumed at controlled 1-week intervals. In the simultaneous condition, participants chose all three snacks at the outset, while those in the sequential condition chose each snack immediately before consumption. On average, simultaneous participants chose a greater diversity of snacks than sequential ones, as evidenced by both a larger number of unique items and a reduced likelihood of choosing their most favored option. This occurred even though simultaneous choices (for future consumption) were preassigned to specific time periods, disallowing diversification as a hedge against shifting preferences (Kreps 1979; Pessemier 1978; Walsh 1995).

In all simulations, we define two choice modes and simulate choosing three items from a set of six alternatives to be consumed (i.e., utility becomes realized) at three separate, predetermined times. In simultaneous choice mode (SIM), all three choices are made now, but only the first chosen item is consumed immediately, and the second and third are consumed in the future. In sequential choice mode (SEQ), the consumer chooses one item at each of the three time periods, immediately before consumption, as follows:
Note that temporal stochastic inflation operates only on choices made for future consumption and so pertains only to the last 2 periods of the SIM condition. For parsimony, a single temporal scaling factor is applied to both periods \( t = 2, 3 \), although this can be readily relaxed to allow for differing degrees of temporal inflation across future time periods.

Simulation Parameters and Choice Generation

We examine the effect of three parameters, corresponding to those in the single-choice, dichotomous case, on the probability of choosing one’s favorite option: degree of temporal stochastic inflation \((\sigma_{\text{FUT}}/\sigma_{\text{MM}})\), relative brand attractiveness \((V_{j})\), and immediate uncertainty \((\sigma_{\text{MM}})\). In each simulation scenario, utilities are generated for all brands, \( j \), according to \( U_{j} = V_{j} + \sigma_{\text{MM}} \varepsilon_{j} \), with \( \sigma_{\text{MM}} \) for immediate choices, \( \sigma_{\text{FUT}}/\sigma_{\text{MM}} \sigma_{\text{MM}} \) for future choices, and \( \varepsilon_{j} \) are independently, identically distributed Gumbel draws (i.e., \( P(\varepsilon_{j} < e) = \exp(-\exp(-e)) \), for all \( j, t \)). Gumbel draws were used for consistency across simulations and with prior logit-based econometric research so that we could avail ourselves of previously established parameter values. All simulations were replicated using normal errors, with substantively identical results (available from the authors).

As explained above, the only inflated periods are the last two in SIM, so that \( \sigma_{\text{SIM},2} = \sigma_{\text{SIM},3} = \sigma_{\text{SIM},4} = \sigma_{\text{MM}} \), but \( \sigma_{\text{SIM},1} = (\sigma_{\text{FUT}}/\sigma_{\text{MM}})\sigma_{\text{MM}} \). Specifications for \( \{V_{j}\} \) will differ in each simulation: homogeneous across simulated consumers in the first and based on actual (heterogeneous) brand preferences in the second. Finally, differences in mean brand attractiveness are operationalized via \( V_{\text{diff}} \). For each simulation scenario, brands are rank ordered by attractiveness, so \( V_{j} \leq V_{j+1} \), and \( V_{\text{diff}} \) represents the average value of \((V_{j+1} - V_{j})\) across brands \( j \) and all simulated consumers. Note that there are five such attractiveness differences in our six-brand simulation scenarios and also that in simulation study 1, \((V_{j+1} - V_{j})\) is identical for all consumers but differs across them in simulation study 2.

Consistent with prior research, we expect that simulated SEQ decision makers are more likely to choose their favorite (highest \( V_{j} \)) option than SIM decision makers (Read et al. 2001; Simonson 1990). In each simulation cell, we tally the proportion of times each person’s most favored brand is chosen (i.e., when \( U_{\text{fav}} \) is the largest of the \( \{U_{j}\} \)) in the SEQ versus SIM choice conditions. The dependent variable in all simulation studies will therefore be diversification differences—measured, similar to the one-shot dichotomous illustration, by differences in the proportion of choices that are the most favored alternative, \( P_{\text{diff}} = P_{\text{fav,SEQ}} - P_{\text{fav,SIM}} \). To disentangle and differentiate deterministic \((V_{\text{diff}})\) and stochastic influences \((\sigma_{\text{MM}}, \sigma_{\text{FUT}}/\sigma_{\text{MM}})\) on diversification differences, we will assess the effects of all three parameters on \( P_{\text{diff}} \). Of particular interest will be the effect of temporal stochastic inflation \((\sigma_{\text{FUT}}/\sigma_{\text{MM}})\) on diversification: we predict that diversification differences will increase with stochastic inflation, holding relative attractiveness and immediate uncertainty constant. Note once again that, because temporal stochastic inflation affects only the last two choices in the SIM condition, all calculations for the SIM condition average one (immediate) choice with two (future) choices incorporating stochastic inflation. This allows us to directly compare our results to prior studies; diversification differences for IMM versus FUT are therefore 50% larger than those reported for SEQ versus SIM.

SIMULATION STUDY 1

Design

Study 1 examines the effects of temporal stochastic inflation, relative brand attractiveness, and immediate uncertainty on the probability of choosing the most favored option and resultant diversification differences. The corresponding parameters, \( \{\sigma_{\text{FUT}}/\sigma_{\text{MM}}, V_{\text{diff}}, \sigma_{\text{MM}}\} \), were manipulated using a \( 3 \times 3 \times 3 \) experimental design, generating 27 simulated choice scenarios with parameter values: \( \sigma_{\text{FUT}}/\sigma_{\text{MM}} = \{1.25, 2.00, 2.75\} \); \( V_{\text{diff}} = \{0.1, 0.5, 1.0\} \); and \( \sigma_{\text{MM}} = \{0.5, 1.0, 1.5\} \). As we will see in simulation study 2, these values were chosen to accord with those reported in prior literature and to provide suitable variation to assess changes in effect strengths. A useful way to conceptualize degree of preference uncertainty is as the ratio \( \sigma_{\text{MM}}/V_{\text{diff}} \) as per figure 1, large values indicate that the mean attractiveness of consecutive brands is close, relative to the degree of immediate uncertainty (stochasticity), and vice versa for small values of the ratio. We deliberately allowed for a broad range of preference uncertainty, from very uncertain (when \( \sigma_{\text{MM}}/V_{\text{diff}} = 1.5/0.1 \)) to very certain (when \( \sigma_{\text{MM}}/V_{\text{diff}} = 0.5/1.0 \)), to examine the range of possible effect sizes under temporal stochastic inflation, with the caveat that extreme ratios (e.g., \( \sigma_{\text{MM}}/V_{\text{diff}} = 1.5/0.1 \)) may be less representative of actual consumer choice scenarios. Data for 1 million simulated consumers were generated for each of the SIM and SEQ conditions, in the manner explained previously, yielding 6 million simulated choices among six alternative brands. This large sample size ensures a very high degree of precision for our simulation results. Brand attractiveness is homogeneous across simulated consumers, with \( V = (j - 1)V_{\text{diff}} \); that is, \( V_{1} = 0; V_{2} = V_{\text{diff}}; \ldots; V_{6} = 5V_{\text{diff}} \). Because there is no preference heterogeneity, brand six is the most favored option (highest \( V \)) for all simulated consumers.

Results

Temporal stochastic inflation had a consistent, positive effect on the magnitude of diversification differences, regardless of the degree of relative attractiveness or immediate uncertainty. The magnitude of \( P_{\text{diff}} \) spanned a broad range across the 27 scenarios (see table 1), from a 0.4% difference when temporal stochastic inflation and the probability of
choosing the favorite option were both relatively low, to a quite substantial 22.7% difference when the favorite option was highly likely (to be chosen for immediate consumption) and temporal inflation was high. Temporal stochastic inflation had a negative effect on the probability of choosing the favorite option in simultaneous choice and, by definition, no effect on sequential choice probabilities. Thus, diversification differences increase with temporal inflation, and this increase is, in fact, monotonic. In addition, the effect strength was influenced by relative brand attractiveness as well as immediate uncertainty—revealing an intriguing interplay of all three preference parameters on the likelihood of choosing one’s most favored option and $P_{\text{diff}}$.

The relative attractiveness of available options altered the effect of temporal stochastic inflation on $P_{\text{diff}}$. As mean attractiveness differences ($V_{\text{diff}}$) increased, for a given level of temporal inflation, $P_{\text{diff}}$ grew larger. Figure 2 illustrates effect sizes observed when we extend the range of simulated $V_{\text{diff}}$ values and serves to spotlight the multivariate results by isolating a variable at a time, as suggested by Irwin and McClelland (2001). As figure 2 shows, the positive relationship between relative attractiveness and $P_{\text{diff}}$ holds up to some maximum diversification difference near 22.7% (for the investigated scenarios; a theoretical maximum value can be cal-

### TABLE 1

**SIMULATION STUDY 1: HOMOGENEOUS PREFERENCES**

<table>
<thead>
<tr>
<th>Temporal inflation $\sigma_{\text{FUT}}/\sigma_{\text{MM}}$</th>
<th>Mean difference $V_{\text{diff}}$</th>
<th>Immediate uncertainty $\sigma_{\text{MM}}$</th>
<th>Favorite chosen (%)</th>
<th>Diversification difference $P_{\text{diff}}$ (%)</th>
<th>Effect range (%)</th>
<th>Effect range (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.25</td>
<td>.1</td>
<td>.5</td>
<td>25.8</td>
<td>24.5</td>
<td>1.3</td>
<td>[.4, 1.3]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>21.0</td>
<td>20.4</td>
<td>.6</td>
<td>[.4, 5.3]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>19.6</td>
<td>19.2</td>
<td>.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>.5</td>
<td>63.4</td>
<td>58.2</td>
<td>5.2</td>
<td>[.2, 5.2]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>41.4</td>
<td>38.0</td>
<td>3.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>33.0</td>
<td>30.6</td>
<td>2.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>.5</td>
<td>86.4</td>
<td>81.9</td>
<td>4.5</td>
<td>[.4, 5.3]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>63.2</td>
<td>58.0</td>
<td>5.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>49.4</td>
<td>45.1</td>
<td>4.3</td>
<td></td>
</tr>
<tr>
<td>2.00</td>
<td>.1</td>
<td>.5</td>
<td>25.7</td>
<td>22.5</td>
<td>3.2</td>
<td>[1.0, 3.2]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>21.3</td>
<td>19.8</td>
<td>1.5</td>
<td>[1.0, 15.3]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>19.6</td>
<td>18.6</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>.5</td>
<td>63.4</td>
<td>48.8</td>
<td>14.6</td>
<td>[5.6, 14.6]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>41.5</td>
<td>32.9</td>
<td>8.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>33.0</td>
<td>27.3</td>
<td>5.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>.5</td>
<td>86.6</td>
<td>71.3</td>
<td>15.3</td>
<td>[11.3, 15.3]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>63.5</td>
<td>48.8</td>
<td>14.7</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>49.6</td>
<td>38.2</td>
<td>11.3</td>
<td></td>
</tr>
<tr>
<td>2.75</td>
<td>.1</td>
<td>.5</td>
<td>26.0</td>
<td>21.9</td>
<td>4.1</td>
<td>[1.2, 4.1]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>20.9</td>
<td>19.0</td>
<td>1.9</td>
<td>[1.2, 22.7]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>19.6</td>
<td>18.4</td>
<td>1.2</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>.5</td>
<td>63.4</td>
<td>43.9</td>
<td>19.4</td>
<td>[7.1, 19.4]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>41.7</td>
<td>30.6</td>
<td>11.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>32.8</td>
<td>25.7</td>
<td>7.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.0</td>
<td>.5</td>
<td>86.4</td>
<td>63.7</td>
<td>22.7</td>
<td>[14.3, 22.7]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0</td>
<td>63.5</td>
<td>44.2</td>
<td>19.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.5</td>
<td>49.7</td>
<td>35.4</td>
<td>14.3</td>
<td></td>
</tr>
</tbody>
</table>
culated for $P_{diff}$; given $n$ items, $k$ choice occasions, and fixing $\sigma_{IMM}$ if both $V_{diff}$ and $\sigma_{FUT}/\sigma_{IMM}$ are “large,” $\text{Prob}(\text{Favorite})$ will be one in SEQ but $(1/k)(1 + (1 - 1/k)(1/n))$ in SIM, yielding a theoretical maximum $P_{diff}$ of 55.6% for our six-item, three-choice decision task. The trend then reverses as attractiveness disparity becomes very large. That is, when attractiveness differences are stark (i.e., very large $V_{diff}$), the probability of choosing the favorite option will be very high whether choosing for now (SEQ) or later (SIM), mitigating the effect of temporal stochastic inflation. In simple terms, an overwhelming favorite will tend to be chosen no matter what. Conversely, choosing from a set of similarly attractive options (e.g., a chocolate lover choosing from a box of chocolates) will tend toward high diversification whether for now or for later, leading to little or no difference. Thus, as predicted in the earlier dichotomous illustration, relative attractiveness has a positive effect on $P_{diff}$, except when $V_{diff}$ is very large, yielding an inverted U-shaped relationship between diversification difference and relative brand attractiveness across the full domain of $V_{diff}$.

Finally, the degree of immediate uncertainty about a brand’s attractiveness ($\sigma_{IMM}$) displayed a clear negative effect on diversification differences over most of the tested range. As $\sigma_{IMM}$ grew larger, the probability of choosing the favorite option decreased for both sequential and simultaneous choice, as did $P_{diff}$. Moreover, the negative effect of immediate uncertainty on $P_{diff}$ was most pronounced when temporal inflation was high.

In conclusion, we found that temporal stochastic inflation always has a positive impact on diversification differences. Both relative attractiveness and immediate uncertainty can exert sizable effects on diversification differences as well. Further, the three parameters can interact to produce a broad range of diversification differences across the 27 simulated scenarios. For example, $P_{diff}$ tends to increase with mean attractiveness differences ($V_{diff}$) but is less pronounced if immediate uncertainty ($\sigma_{IMM}$) is high or temporal stochastic inflation ($\sigma_{FUT}/\sigma_{IMM}$) is low and can even reverse if $V_{diff}$ is extreme. The $P_{diff}$ will decrease with immediate uncertainty ($\sigma_{IMM}$), especially when attractiveness differences ($V_{diff}$) are moderate (neither low nor high) and temporal stochastic inflation ($\sigma_{FUT}/\sigma_{IMM}$) is high. Finally, the effects of temporal stochastic inflation on diversification differences are least pronounced when brand attractiveness is very similar (low $V_{diff}$) or very dissimilar (high $V_{diff}$); they are most pronounced when immediate uncertainty ($\sigma_{IMM}$) is relatively low.

Preference Heterogeneity Effects

Because study 2 will make use of real, heterogeneous preferences, we conducted supplementary simulations that manipulated preference heterogeneity as well the three parameters from this study (results available from the authors). Heterogeneity was of the most common type used in choice studies, a random coefficient or single normal component specification (Andrews, Ainslie, and Currim 2002), and was operationalized by adding a standard normal draw, multiplied by one of {0, 0.25, 0.5, 1}, to each simulated consumer’s attractiveness value for each brand; the value of zero was included as a check and exactly reproduced study 1. All findings from study 1 were broadly replicated in the presence of preference heterogeneity; critically, temporal stochastic inflation was positively related to diversification differences. The results of this supplemental simulation are summarized graphically in figure 3 (for $\sigma_{IMM} = 1$) and can be summed up verbally as follows: increasing preference heterogeneity slightly dampens effects on $P_{diff}$; when $V_{diff}$ is very large, a negative effect of increasing heterogeneity is detectable, but small; the effect is barely detectable with low attractiveness differences; and heterogeneity never causes the direction of the difference between SEQ and SIM to change. That is, heterogeneity does not alter the main results of study 1, even when its degree is pronounced.

SIMULATION STUDY 2

Design

Simulation study 1 employed hypothetical, homogeneous preferences. Although preference heterogeneity alone cannot drive the substantive results of study 1, it is possible that, because the parameters chosen for the study did not stem from measurement, results do differ in magnitude from those likely to occur in real choice contexts. The goal of study 2 is thus to test whether the pattern of results in study 1 are robust to naturally occurring empirical features of individual consumer preferences. We thus collect preference data, capturing its properties parametrically; we can then generate simulated choices using choice model coefficient values stemming from prior literature. Because these data reflect the preferences of real participants, mean attractiveness

![Figure 3](image-url)
difference ($V_{att}$) and immediate uncertainty ($\sigma_{IMM}$) parameters cannot be manipulated directly, as in simulation study 1. Instead, we use a 5 × 4 experimental design, manipulating (as before) temporal stochastic inflation ($\sigma_{FUT}/\sigma_{IMM}$), as well as an attractiveness weighting parameter that serves as a proxy for $V_{att}$, as described below; for ease of presentation, $\sigma_{IMM}$ is normalized to one, so $\sigma_{FUT}$ represents the temporal stochastic inflation factor ($\sigma_{FUT}/\sigma_{IMM}$).

We simulated experimental participants choosing three snacks from among the six snacks used in the between-subjects designs of Simonson (1990) and Read and Loewenstein (1995). To do so, we collected measures of individual preference for six snacks that align closely with their reported stimuli: Austin cheese crackers, Doritos tortilla chips, Hershey’s chocolate bar with almonds, Oreo cookies, Planters peanuts, and Snickers candy bar. One hundred one undergraduate students at the University of Michigan participated to earn credit in an introductory marketing course.

Brand attractiveness was measured by asking participants to rate how much they liked each snack using an 11-point Likert scale (1 = dislike very much, 11 = like very much), consistent with prior research. Attractiveness differed considerably across the snacks, with mean rating values ranging from 5.54 for Austin cheese crackers to 8.55 for Snickers. Mean rating values had a broader span when computed for participant-specific favorites, second favorites, and so forth, ranging from 10.29 for favorites to 9.19 for second favorites (a difference of 1.10) to 3.71 for least favorites, implying $V_{att} = (10.29 - 3.71)/5 = 1.32$ across all six snacks.

**Simulated Choice Generation**

Because the attractiveness data were ordinal, we proceeded as follows. First, we estimated the latent multivariate normal distribution underlying the (discrete ordered) brand attractiveness data. Next, we generated a large number of draws, and “thresholded” them via estimated cutoffs, so the proportions in each choice category matched the real data. That is, the proportion of (say) those rating Snickers as nine (on the 1–11 scale) was the same for the large master list of simulated draws and the actual attractiveness data. In this way, the structure of the generated attractiveness data is consistent with a multivariate ordered probit model (Lawrence et al. 2006). This process accomplishes four goals: (1) it captures scale usage and the empirical attractiveness distributions for each brand, (2) it captures correlations in attractiveness across the six brands, (3) it mitigates overreliance on any one (real) participant’s idiosyncratic preferences, and (4) large samples can easily be generated.

For each simulated participant, we calculate a (latent) deterministic utility for all six brands on any particular choice occasion, adding stochastic draw $\sigma e_{j,n}$ according to the specification (suppressing consumer-specific subscripts for simplicity):

$$U_{n} = V_{j,n} + \sigma_{e_{j,n}} = \beta_{j} + \beta_{ATT}ATT_{j,n} + \sigma_{e_{j,n}},$$

where $\beta_{j}$ is the brand-specific constant for snack $j$, $ATT_{j,n}$ is a participant’s attractiveness rating for snack $j$, and $\beta_{ATT}$ relates attractiveness to utility. We allowed for two assumptions regarding the brand-specific constants: (1) there are no brand-specific constants, so that all $\beta_{j}$ equal zero, and (2) brand-specific constants take values observed in prior research (Simonson 1990, experiment 2): {0.15, −0.10, 0.53, 0, −0.18, 0.45} for cheese crackers, tortilla chips, Hershey’s, Oreo, peanuts, and Snickers, respectively; one brand’s (here, Oreo) constant is set to zero for identification.

We use a range of values for $\beta_{ATT}$, {0.2, 0.4, 0.6, 0.8, 1.0}, for three reasons: (1) to provide benchmarks for the effects of attractiveness on utility, (2) to align well with study 1, and (3) to accord with prior findings. Simonson (1990) used two 11-point preference measures, attractiveness (ATR) and liking (LIK), with mean reported coefficient values $b_{ATR} = 0.555$, $b_{LIK} = 0.575$ across SIM and SEQ. Because LIK and ATR are correlated, coefficients should not simply add; our maximal simulation value, $\beta_{ATT} = 1$, corresponds to a correlation of 0.6. Recall that, because $\beta_{ATT} = 1$ translates into a $V_{att}$ value of 1.32, simulated values of {0.2, 0.4, 0.6, 0.8, 1.0} correspond to $V_{att} = $ {0.26, 0.53, 0.79, 1.06, 1.32} when brand-specific constants are zero, and to nearly identical values for the nonzero set of brand-specific constants.

The only parameter in our simulation that is not based on prior econometric results, therefore, is the focal quantity in our study, the degree of temporal stochastic inflation, $\sigma_{FUT}/\sigma_{IMM}$, with values of {1.5, 2.0, 2.5, 3.0}.

Choice on a particular occasion ($t$) is, as always, the item with the largest value of ($U_{j}$) across brands $j$. This is carried out for both the SIM and SEQ choice conditions using the same simulated respondent preferences, to eliminate any between-condition preference differences. Draws of $e_{j,n}$ are made separately across times ($t$), brands ($j$), and conditions, as they must be. We generated 500 simulated consumers, so that our simulated data consist of 500 sets of three choices from among six snacks for each of the SIM and SEQ conditions (a total of 3,000 simulated choices). Larger numbers of simulated respondents yielded equivalent empirical findings.

**Results**

Our numerical results were substantively identical, and very close in magnitude, whether assuming equal (i.e., zero) or unequal brand-specific constants, so we report here only the latter, as those accord with prior literature. Diversification differences were found in all scenarios, and these differences increased with temporal stochastic inflation, replicating the findings of study 1 (see table 2). This positive effect of temporal inflation on $P_{IMM}$ was magnified as the weight ($\beta_{ATT}$) placed on attractiveness increased: differences peak (at 22.0%) when attractiveness is most heavily weighted ($\beta_{ATT} = 1.0$) and temporal inflation is highest ($\sigma_{FUT}/\sigma_{IMM} = 3.0$). Diversification differences were smallest (2.4%) when attractiveness was least heavily weighted ($\beta_{ATT} = 0.2$) and temporal inflation was low ($\sigma_{FUT}/\sigma_{IMM} = 1.5$).
Choosing items for future consumption is a ubiquitous consumer activity. Consumers’ tendency to diversify their choices more for future than for present consumption has been demonstrated to be a robust phenomenon and to occur in a variety of situations. Prior research has identified future preference uncertainty, stemming from anticipated changes in underlying tastes, as a source of diversification differences (Simonson 1990). An alternative perspective proposes that preference uncertainty is greater when choosing for the future because of increased stochastic noise around the mean attractiveness of each available item, and this leads to diversification differences. We therefore examined two basic influences on preference uncertainty during choice: (deterministic) differences in the mean utilities of available options and (stochastic) variances of those utilities. Regardless of how preference uncertainty is enhanced—whether by decreasing mean differences or increasing stochastic variation—choice probabilities are drawn inward, to a more uniform distribution, and the probability of choosing the favorite option on every choice occasion decreases. And this, in turn, leads to greater diversification in repeated choice.

Previous research correctly asserted that anticipated temporal shifts in the deterministic components of utilities could generate diversification differences. Our findings demonstrate that such anticipated shifts are indeed sufficient but not necessary; rather, if time delay between choice and consumption increases stochastic variation in utilities (and thereby preference uncertainty), sizable diversification differences can result, even in the absence of (deterministic) preference shifts. It is also quite plausible that both deterministic and stochastic forces may act in concert to increase diversification when choices are made for future consumption.

A series of simulation studies indicated that diversification differences on the order of those previously reported can arise, in whole or in part, from the greater stochastic variation intrinsic to choices made for the future. Such effect sizes were observed when “real” values were used for brand preferences and relevant random utility model coefficients and, intriguingly, in the presence or absence of substantial preference heterogeneity. Diversification differences are also influenced by characteristics of the options available in the choice set: simulations revealed that the magnitude of diversification differences can be attenuated when the relative attractiveness of available choice alternatives is either very similar or very dissimilar. A strongly favored option has a high likelihood of being chosen whether for now or for the future, leading to low diversification in both conditions, and thus a small diversification difference. Conversely, choosing from an assortment containing a weak favorite will tend toward high diversification, regardless of whether choosing for now or for the future, also leading to small diversification differences. Direct empirical tests of this attenuation of diversification differences are ripe for further study. Further research is also needed to empirically estimate temporal inflation factor magnitude, as well as how it might vary with time delay. We used a common inflation factor ($\sigma_{\text{FUT}}/\sigma_{\text{IMM}}$)
across all future time periods in simultaneous choice; yet, in reality, the degree of inflation may itself increase or wane over time. Because our summary measures are averaged across time periods, reported values of $\frac{d_{FIM}}{d_{JMM}}$ are akin to means (for $r > 1$); nonetheless, additional studies should assess whether this operational assumption is warranted for real-world choice sequences.

Simulation, by nature, cannot speak to the thought processes underlying choice or their purported rationality. Future research would do well to examine whether diversification differences arise, in whole or in part, due to biased thought processes. One possibility involves econometrically assessing various contributory mechanisms leading to diversification differences. Yet typical (homoscedastic) analysis methods rule out stochastic differences: not only can they not detect them, but they explicitly force the degree of uncertainty (stochasticity) to be the same at all times and for all choices. Any statistical analyses of experimental data require a framework that allows competing theories of diversification differences to be unambiguously tested. A choice model that relaxes the constant variance assumption allows for precisely such direct tests of the effects of uncertainty on choice and diversification, effects potentially conflated via traditional methods of analysis. Modifications of commonly applied discrete choice models could disentangle deterministic (e.g., mean attractiveness shifts) and stochastic (e.g., temporal inflation) effects. These are conceptually distinct and, as our series of simulations show, have clearly demarcated effects vis-à-vis diversification.

Although we have modeled preference uncertainty via the stochastic component of latent utility, another possibility—one allowing direct tests—is a specification incorporating self-reported perceived uncertainty (or, analogously, confidence) within the deterministic component of utility. While self-reported confidence has been measured in prior research examining simultaneous choice (Simonson 1989), no analogous measure for sequential choice, or direct test of deterministic versus stochastic sources of future preference uncertainty, was performed. Regardless of the underlying model or econometric approach, results are unlikely to be attributable entirely to either deterministic or stochastic effects, and a key issue for future research is to determine the relative influence of these two sources to the overall strength of diversification effects in general.

In conclusion, stochastic preferences can play an important role in understanding why consumers tend to diversify more when choosing for the future, as well as when the analyst might expect to observe them doing so. Future preference uncertainty, driven by inflated stochastic utility variation, leads to greater diversification, while both the relative attractiveness of available options and brand attractiveness uncertainty moderate the size of diversification differences. Future investigations require tight experimental controls and process measures to disentangle these and other effects in “real” choice data, as well as an appropriate statistical model. The present article offers a first step in suggesting the sorts of effects to be anticipated in experimental and field data on consumer choice and its diversification.

REFERENCES


Lawrence, Earl, Derek Bingham, Chuanhai Liu, and Vijayan Nair (2006), “Bayesian Inference for Ordinal Data Using Multivariate Probit Models,” working paper, Department of Statistics, University of Michigan, Ann Arbor, MI 48109.


Read, Daniel, George Loewenstein, and Shobha Kalyanaraman (1999), “Mixing Virtue and Vice: Combining the Immediacy
Effect and the Diversification Heuristic,” *Journal of Behavioral Decision Making*, 12 (December), 257–73.


