DEAL-BREAKERS & DEAL-MAKERS:
A COGNITIVELY PLAUSIBLE MODEL OF MATE CHOICE

Elizabeth Bruch
Department of Sociology—University of Michigan

Kee Yeun Lee
Fred Feinberg
Ross School of Business—University of Michigan

ABSTRACT: Despite the behavioral nature of online dating data, past analysis do not in any way represent the underlying activities of mate seekers. We present a statistical model of mate choice behavior that draws on insights from decision theory, marketing research, and cognitive science. The model assumes an actor with partial information, uncertainty about the most desirable outcome, and difficulty comparing more than a handful of alternatives based on a small number of attributes. The substantive application is mate choice, as observed on an online dating site. This work makes several contributions. From a theoretical standpoint, we lay the groundwork for a model of individual action that is empirically plausible, statistically tractable, and amenable to analytic research. With regard to our substantive application, mate choice, our model allows for a far more nuanced account of mate preferences and mate search strategies than has been possible in the past. Methodologically, this study represents a first effort to develop a statistical framework for harnessing the detailed, observational online activity data increasingly available for social research to better understand how people make decisions.

1. MOTIVATION

Many social outcomes are driven by a sequence of individual decisions. For example, patterns of assortative mating are a product of men and women's choices about whom to date or marry. Residential segregation results from households, families, or individuals' decisions about where to live. Obesity results in part from decisions related to food consumption and exercise. Sociologists typically argue that individuals' choices are driven by some combination of preferences that determine the relative attractiveness of available options, and opportunities or constraints that limit what options are available (Zeng and Xie 2008; Bruch and Mare 2012). However, empirical researchers rarely represent individuals' behavior or decision-making process explicitly. In quantitative studies, the standard approach is to decompose variation in some individual outcome of interest into portions attributable to different "explanatory" covariates. Causal relationships are attributed to variables rather than human actors. The statistical model used in the analysis is rarely if ever a plausible model of the underlying behavior or decision-making process that gave rise to the social phenomenon under investigation. As a result, these analyses are divorced from the actions or activities that lead to that particular outcome (Abbott 1992). Without an explicit representation of individuals as actors, empirical sociology is increasingly disengaged from social theory (Coleman 1986, p. 1327; Sörensen 1998). Especially in light of the burgeoning interest in analytical studies that link micro behavior and macro-level outcomes, there is a need for empirically defensible, quantifiable models of individual behavior (Hedström 2005).

One powerful solution is to assume that individuals act according to the postulates of rational choice theory (Goldthorpe 1996; Hedström and Swedberg 1996). Rational choice theory can be roughly characterized by its view of individual behavior. The theory assumes that people with well defined preferences assign a utility or subjective value to each option in a set of choice alternatives, and then choose the alternative that best satisfies their preferences (Kroneberg and Kalter 2012, p. 74). Individuals are assumed to have unlimited ability or skill in computation that enables them to weigh the costs and benefits of each choice option. Rational choice theory's appeal rests in part on its specificity with regards to individual action, and its ability to replace variable-driven, ad-hoc empirical analysis with more theoretically grounded approaches. It is difficult to overstate the centrality or importance of this model of individual behavior in the social sciences. Whether as an object of love or hate, it provides the theoretical motivation for a great deal of influential work in sociology, economics, anthropology, political science, and psychology (Berger 1969; Kaiser and Hechter 1998; Somers 1998; Ostrom 1998; Vaughan 1998; Coleman 1990). Statistical models of choice behavior used in the social sciences also assume a fully informed, rational, utility-maximizing individual (McFadden 1978, p. 4).

However, over the past several decades, psychologists and decision theorists have convincingly shown that that the rational choice model is a poor representation of how real people make decisions. The fundamental critique is that decision-making, as envisioned in the rational choice paradigm, would make overwhelming demands on our capacity to process information (Bettman 1979; Miller 1956; Payne 1976). This work endorses *bounded rationality* (Simon 1955), the idea that decision-makers have limitations in their capacity for processing information. These include limited time for learning about choice alternatives, limited working memory and limited computational capabilities. As a result, a great deal of behavior is habitual, automatic, or governed by simple rules or heuristics. In recent years, a number of sociologists have called for realistic theories of action that recognize the cognitive limitations of individuals (e.g., Hedström 2005; Esser 2009). One challenge, however, is that alternative approaches to modeling individual behavior are not formalized into a quantifiable model of decision-making. Thus, even if scholars can theorize potential alternatives (e.g., Hedström 2005, Chapter 3), these alternatives cannot be easily incorporated into empirical research. Thus studies seeking to model individual behavior or link empirical descriptions of individual behavior to macro-level social processes revert back to the unrealistic assumptions of the rational choice model.

Researchers in the field of marketing have, for the past thirty or more years, worked out sophisticated statistical models of decision-making, but these have not been applied to social contexts. Given that both disciplines concern themselves with understanding human behavior, there is fertile territory at their intersection: extending individual-level choice models from marketing to a variety of thorny, open problems in sociology and cognate disciplines. The aim of this paper is to present and estimate a statistical model of choice behavior that draws on insights from decision theory, marketing research, and cognitive science. The model assumes an actor with partial information, uncertainty about the most desirable outcome, and difficulty comparing more than a handful of alternatives based on a small number of attributes. The substantive application is mate choice, as observed on an online dating site.

This work makes several contributions. From a theoretical standpoint, we lay the groundwork for a model of individual action that is empirically plausible, statistically tractable, and amenable to analytic research. With regard to our substantive application, mate choice, our model allows for a far more nuanced account of mate preferences and mate search strategies than has been possible in the past. For example, we show that some attributes act as “deal-breakers” to screen out large numbers of undesirable prospective partners. Methodologically, this study represents a first effort in sociology to develop a statistical framework for harnessing the detailed, observational choice data increasingly available for social research to better understand how people make decisions. Historically, individual behavior was studied using surveys, which tend to reify variables-based explanations. The vast amounts of behavioral data from cell phones and the internet (e.g., activities on online dating sites, Facebook, and other electronic social forums) make it now possible to study human behavior with an unparalleled richness of detail and granularity. But our statistical techniques and theoretical models have lagged behind. Our work illustrates in one specific case how one can harness the richness of observational data to glean new insights about human behavior.

2. EMPIRICAL STUDIES OF DECISION-MAKING

A large body of research in cognitive psychology has confirmed that individuals are "limited information processing systems" (Newell and Simon 1972). In contrast to traditional models that assume unlimited cognitive capacity, empirical studies show that people can only compare only a small number of potential options at any given time (Miller 1956; Payne, Bettman, and Johnson 1993). As a result, people use heuristics that serve to keep the information-processing demands of a task within the bounds of their limited cognitive capacity. Heuristics are "problem-solving methods that tend to produce efficient solutions to difficult problems by restricting the search through the space of possible solutions, on the basis of some evaluation of the structure of the problem" (Braunstein 1972, p. 520). While there are some debates about the degree to which heuristics outperform rational, optimizing decision-making in real life situations (Gigerenzer and Gaissmaier 2011; Gigerenzer and Brighton 2009), it is generally recognized that the central process in human problem solving is to apply heuristic methods to carry out highly selective searches of problem spaces (Newell and Simon 1972).

Consideration Set Models

How people search within and then choose from a large space of potential alternatives is a central focus of behavioral decision theory in general, and of academic marketing research in particular. Commencing with the pioneering work of Howard and Sheth (1969), scholars have accumulated substantial empirical evidence for the idea that decisions are typically made sequentially, with each stage reducing the set of potential options (Swait 1984; Roberts and Lattin 1991; Roberts and Lattin 1997). For a given individual, the set of potential options can first be divided into the set that he or she knows about, and those that he or she is unaware. This "awareness set" is further divided into options the person would consider, and those that are irrelevant or unattainable. This smaller set is referred to as the consideration set, and the final decision is restricted to options within that set. Research in consumer behavior suggests that the decision to include certain alternatives in the consideration set can be fundamentally different than the final choice decision (Shocker et al. 1991). In many cases, consumers use simple rules to restrict the energy involved in searching for options, or to eliminate products from future consideration. For example, an individual purchasing milk at the supermarket might only consider organic brands, or containers below a given price range. Essentially, people favor less cognitively taxing rules that use a small number of choice attributes earlier in the decision process to eliminate almost all potential alternatives (a process known as "consideration set formation" in the marketing literature), but take into account a wider range of choice attributes when evaluating the few remaining alternatives for the final decision (Payne, Bettman, and Johnson 1993).

In multistage decision-making, once the decision maker has narrowed down his or her options to a few alternatives, the final choice decision may allow different dimensions of alternatives to be compensatory; in other words, a less attractive value on one attribute may be offset by a more attractive value on another attribute. However, a large body of decision research demonstrates that strategies to screen potential options for consideration are non-compensatory; a decision-maker's choice to eliminate from or include for consideration based on one attribute will not be reversed based on the value of other attributes. In other words, non-compensatory decision rules act as "deal-breakers" or "deal-makers" that serve to eliminate many potential alternatives from consideration. Thus, compensatory decision rules are "continuous", while non-compensatory decision rules are discontinuous or threshold. This implies potentially dramatic behavior changes as a choice qualifies for or disqualifies from inclusion in the consideration set (Swait 2001; Gilbride and Allenby 2004).

Decision Strategies used in Heuristic Choice

Compensatory Rules: The implicit decision rule used in statistical models of individual choice and the normative decision rule for rational choice theory is the weighted additive rule. In this choice regime, decision-makers compute a weighted sum of all relevant attributes of potential matches. Choosers develop an overall evaluation of each choice alternative by multiplying the attribute weight by the attribute level (for each salient attribute), and then sum over all attributes. This produces a single utility value for each alternative. It is generally assumed that the alternative with the highest value is selected. Any conflict in values is assumed to be confronted and resolved by explicitly considering the extent to which one is willing to trade off attribute values, as reflected by the relative importance or beta coefficients (Payne, Bettman, and Johnson 1993: 24). This rule involves substantial computational effort and processing of information.

A simpler compensatory decision rule is the <u>frequency of good and bad features</u> (Alba and Marmostein 1987), known to most of us as a "pro and con" list. This strategy ignores information about the relative importance of each attribute. To implement this heuristic, choosers must identify cutoffs that specify whether an attribute value is desirable or undesirable. Then the decision maker simply counts up the number desirable versus undesirable attributes. Strictly speaking, the frequency of good and bad features rule forces people to make trade-offs among different attributes. However, this rule is much less cognitively demanding than the weighted additive rule, as it does not require people to specify precise weights associated with each attribute. On the other hand, both rules require people to examine *all* information for each alternative, determine the sums associated with each alternative, and compare those sums.

Non-Compensatory Rules. Non-compensatory decision rules are computationally far less intensive than compensatory decision-rules, as they do not require the chooser to explicitly consider all salient attributes of an alternative, assign numeric weights to each attribute, or compute weighted sums in one's head. There are a number of different non-compensatory decision rules. For example, choice sets formed by a <u>conjunctive</u> decision rule require that an alternative must be acceptable on one or more salient attributes. For example, in the context of residential choice, a house that is unaffordable will never be chosen, no matter how attractive it is. Similarly, a man looking for partners on an online dating website may only search for women who are within a 25-mile radius, under the age of 40, and without kids. Potential partners that are unacceptable on even one dimension are eliminated from consideration. So conjunctive screening rules identify "deal-breakers;" being acceptable on all deal-breakers is a necessary but not sufficient criterion for being chosen. Choosers may be indifferent among alternatives that pass the screening rule, or subsequently implement a compensatory rule to adjudicate among this smaller number of possibilities.

A <u>disjunctive</u> rule dictates that an alternative is considered if *at least one* of its attributes is acceptable to chooser i. For example, a sociology department hiring committee may always interview candidates with two or more *American Journal of Sociology* publications, regardless of their teaching record or quality of recommendations. Similarly (as especially evocative, and therefore somewhat fanciful examples), a disjunctive rule might occur for the stereotypical "gold-digger" or "gigalo", who targets all potential mates with very high incomes regardless of their other qualities. Thus, disjunctive decision rules identify attributes that are "deal-makers;" qualifying on any one of them is sufficient for further consideration. Both disjunctive and conjunctive decision rules are explicitly non-compensatory; that is, a person who does not meet these criteria has little hope of somehow making up for deficiencies with attractive qualities on other dimensions. Thus, these decision rules are cognitively far less taxing than compensatory rules. The decision maker need only evaluate the attributes that define cutoffs in order to make a decision. The fewer attributes are used to evaluate a choice alternative, the less cognitively taxing the rule will be.

Sociological Implications of Decision Strategies

These micro-details of decision-making would be solely of psychological interest, except for the fact that they likely have important implications for macro-level social patterns of inequality and segregation. A multistage decision process that eliminates many potential alternatives in the initial stage and then only later allows for a more holistic evaluation will likely have very different aggregate implications for social inequality and social differentiation than a single-stage decision rule that takes a holistic approach. For example, in residential segregation an important mechanism for stable integration is the cumulation of small, unlikely mobility decisions (Bruch and Mare 2006, 2009). If individuals using a screening rule *never* consider neighborhoods above some threshold number of black residents or below a given poverty rate, this cumulation will never occur. Similarly if low-income students applying to college only consider community colleges or four-year institutions close to home, or will only consider colleges that they have heard of, these students will never be swayed by generous financial aid packages available at more selective but physically and socially distant institutions (Hoxby and Avery 2004). With regard to our current application, mate choice, individuals on an online dating site that only search for or browse same race potential partners will never be swayed by out groups' brilliant and thoughtful prose, or high levels of educational or social achievement. Thus, non-compensatory decision rules may be a key mechanism explaining why durable patterns of inequality or segregation can persist even in the absence of institutional barriers to social integration or social mobility.

3. RESEARCH ON MATE PREFERENCES AND MATE CHOICE

Up until quite recently, there was little data to study mate choice. The dominant strategy that scholars used was to examine coefficients from loglinear models estimated from a cross-classified table of couples' attributes. This information is typically obtained from data on marriages, but may also come from cohabiting partners or other relationships. The focal parameters provide information on what kinds of matching patterns persist after accounting for the pairings that would be expected on the basis of random sorting given the joint distribution of men and women's attributes. The problem is that these statistical models cannot disentangle individuals' preferences or desires from the structural constraints imposed by the marriage market (Logan, Hoff, and Newton 2008; Logan 1996). Also, by specifying the unit of analysis to be the match, this approach ignores the two-sided nature of the marriage market. In other words, data on successful matches cannot distinguish between men and women's preferences for mates. It is likely that men and women have different preferences for attributes of partners (England and McClintock 2009), and also men and women may have different tolerance for remaining single in the face of an unacceptable match.

Over the past few years the increased availability of behavioral data from online dating web sites has led to a number of studies to use patterns of early stage mate choice—that is, who browses, contacts, or responds to whom—to estimate models of mate preferences. For example, using a German online dating website to examine patterns of educational assortative mating, Skopek and colleagues (Skopek, Schulz, and Blossfeld 2011) find that both men and women match on education, and preference for a partner of similar education is most pronounced among the highly educated. A couple of studies have used American online dating data to investigate men and women's preferences for mates. Consistent with the work by Skopek and colleagues, they find that men and women have strong preferences for a partner who shares their education, but document substantial differences in how men and women assess partners with more or less education than themselves (Hitsch, Hortaçsu, and Ariely 2010). With regards to race, these studies suggest that both matching and competition play important roles in mate choice decisions (Lin and Lundquist 2013).

However, in all cases, the focus is on "preferences" as reflected in the relative magnitude and significance of beta coefficients in a statistical model. The statistical technique used in these studies assumes a single-stage decision process, in which mate-seekers with unlimited time and computational resources consider every single potential mate in their metropolitan area using a compensatory model. Thus, despite the behavioral nature of the online dating data, past empirical analyses do not in any way represent the underlying activities that give rise to choice outcomes. Researchers instead impose the same implausible assumptions and statistical techniques that have been used for decades to analyze survey data. Behavioral data provide new opportunities to develop theoretical models of individual choices, but this requires a new set of statistical models and new theories of behavior.

Especially on online dating sites where users are confronted with potentially hundreds of potential partners, mate seekers are likely to rely on multistage and potentially non-compensatory screening rules. For example, men who want to start a biological family of their own might not even consider a woman past childbearing age, regardless of her other attributes. Similarly, white women browsing potential matches may pass over any profile where the photo identifies the user as African American, never clicking through to additional information regarding occupation, education, and cultural values. With a multistage model with decision rules, we can assess whether existing hypotheses are supported by the data, and the boundary conditions where each hypothesis holds. In addition, we can find new relationships among attributes and identify new hypotheses that relate to the screening rules that people use.

4. A STATISTICAL MODEL OF MATE SEARCH AND MATE CHOICE

Our main goal is to specify a "cognitively plausible" model of mate choice that captures sociologically relevant features of the search and evaluation process. The model is presented for heterosexual mate choice, but can easily be adapted to same sex partners. We treat the final outcome as a binary variable indicating whether a man or woman sends a first contact message to a user of the opposite sex.[1] An intermediate outcome is a set of profiles that the user browses while searching for mates. Thus, model allows for decisions to be made in multiple stages, and also evaluates empirical evidence in favor of compensatory and non-compensatory decision rules at each stage. In addition, the model allows us to assess differential willingness to "settle" at this early stage of mate choice. While a number of marketing studies have estimated choice models with non-compensatory decision rules (e.g., Gilbride and Allenby 2004), most assume that decision makers use the same rule (e.g., compensatory or non-compensatory) to valuate all attributes of choice alternatives. Two past studies have allowed for different decision rules to apply to different attributes. Swait (2001) uses piecewise linear functions to estimate response curves that allow decision-makers to penalize, but not eliminate, alternatives that fail to meet a conjunctive cutoff. However, he uses self-reported cutoffs from stated preference data to identify the cutpoints. Our goal is to estimate the response function, including any non-compensatory cutoffs, using observational data.

The study most similar in spirit to our approach, Elrod et al. (2004) uses a non-rectangular hyperbolic function to specify decision rules that allow for an explicit parameterization of compensatory versus non-compensatory functions in observational data. Their model has the advantage that it provides a clean and precise statistical test for whether a decision rule is conjunctive, disjunctive, or compensatory. However, this elegant approach comes at the cost of enacting some fairly restrictive simplifying assumptions. First, they assume that all compensatory decision rules are linear response functions; non-linear is conflated, if not equated, with non-compensatory. But this seems implausible in the case of mate choice: for example, some mate seekers may find potential partners who are divorced to be disproportionately unattractive while trading this off against other things. In addition, the non-rectangular hyperbola only allows for monotonic response functions, but there is reason to believe that a number of attributes have a non-monotonic response function (e.g., women tend to have a zone of acceptability near their own age,

[1] Another possible outcome is whether a user responds to a message from a potential mate. While response patterns are important, they are difficult to interpret. For example, a user may email a potential suitor to say "thanks, but no thanks." In addition, the probability of a response may depend nontrivially on other messages one has received as well as unmeasured characteristics of the message itself (e.g., wittiness of opening line; as well as spelling, grammar, and punctuation). As a simplifying first step, we focus only on the very first stages of the choice process: searching for potential mates, and sending a first contact message. Later work will explore how site users' responses to overtures from potential partners depends on feedback they receive other users about their relative attractiveness.

finding much younger or much older potential mates a less good fit).

Finally, Elrod et al.'s (2004) cutoff points are derived from the maximum and minimum observed values, without any statistical error. This assumption only makes sense when decision makers must follow strict rules, as are sometimes imposed in college admissions. By contrast, our model allows for the identification of such "near non-compensatory" rules. This distinction is important. Were a deal-breaker truly inviolable, it would be a simple and tautological matter to pull them from observed data. For example, if a particular site user wrote only to people above a certain age, we might declare that being below that age is a deal-breaker. However, this would be premature, as determining this would depend on examining the pool of potential recipients. It would also ignore important statistical background information: if that respondent wrote to 100 other users, 99 of whom were over fifty, and one of whom was twenty-five, the model should not merely spit out that a deal-breaker age was anything over the much lower figure. In other words, there needs to be an *error model* and some notion of being able to statistically test various regions for differing response propensities. In other words: a model based approach. In the next section, we show how one can use information on mate seekers' activities on the site (browsing and writing to potential mates) to identify mate choice decision rules. To that end, we now define generic utility functions for each portion of the two-stage process: browsing and writing.

Utility Functions

It is ironic that decision rules which are cognitively demanding for the decision-maker are actually easier to model statistically than simpler, more "cognitively plausible" strategies. For example, the weighted additive model can be easily estimated using linear regression techniques. On the other hand, non-compensatory decision rules that imply: (a) abrupt changes in the relative desirability of potential partners as an attribute passes over an acceptability threshold; and (b) that an attribute has a disproportionate effect on choice outcomes over some region of values do not have an obvious modeling solutions. Ideally, one would seek to impose a fully nonparametric account: a model that can have arbitrary complexity in utility shape, achieved via a modeling framework whose degree of parameterization is not set in advance. Such a framework has been developed before (e.g., Kim et al. 2007), but has strong data requirements (e.g., many observations per respondent), high computational costs, and has not been adapted to multistage, highly multiattribute decisions. The key benefit provided by the nonparametric approach is that utility "shapes" can have multiple regions, with a different degree of trade-off between an attribute and (dis)utility in each.

Among the major findings of Kim et al. (2007) were: (1) that piecewise *linear* splines sufficed to capture utility as well as allowing segments of the spline function to be quadratic or higher; and (2) that, for the vast majority of participants in multiple data sets, the modal number of interior knots was 2. Specifically, in a conjoint application with 6 attributes, all 6 were best captured by 2 interior knots (see their Fig. 1); and in three scanner data sets, the modal number of knots in each was 2 or fewer (see their page 349, column 2). Although one must exhibit caution in exporting the findings from their study to a novel context, we propose that a flexible yet relatively parsimonious account of utility can be piecewise linear, so long at it allow for *no fewer than two* interior knots. We adopt this convention here, emphasizing that, although the usual linear utility specification requires two parameters (slope and intercept), a two-knotted piecewise linear utility spline requires six, since each additional utility segment grafted onto a base (linear) function requires two new parameters: one for the location of the knot, and another for the slope change coincident with that knot. Note that this does *not* affect the intrinsically discrete nature of how purely categorical variables are typically handled, which we adopt here for both comparability and maximal flexibility.

In line with the preceding discussion, the utility function for browsing is decomposed into three portions: an intercept; a two-knotted piecewise linear spline for continuous (or ordinal) attributes (e.g., age group); and a conjoint-like representation for intrinsically categorical attributes (e.g., ethnic group); as follows:

$$V_{ij}^{B} = \beta_{0i}^{B} + \sum_{k=1}^{K}\left[\beta_{1ik}^{B}x_{jk}^{B} + \beta_{2ik}^{B}\left(x_{jk}^{B} - \delta_{1ik}^{B}\right)_{+} + \beta_{2ik}^{B}\left(x_{jk}^{B} - \delta_{2ik}^{B}\right)_{+}\right] + \sum_{l=1}^{L}\boldsymbol{\gamma}_{\boldsymbol{il}}^{\boldsymbol{B}}\boldsymbol{x}_{\boldsymbol{jl}}^{\boldsymbol{B}},$$

$$\text{where } (y)_{+} = \begin{cases} y & \text{if } y \geq 0 \\ 0 & \text{if } y < 0 \end{cases} \text{ and } \delta_{1ik}^{B} \leq \delta_{2ik}^{B}. \qquad (1)$$

Here, V_{ij}^{B} stands for the systematic part of the utility for user *i* of browsing potential mate *j*. It is specified as a linear additive model with three components: 1) β_{0i}^{B} (an intercept term); 2) the sum of the utilities of *K* continuous attributes; 3) the sum of the utilities of L discrete attributes. As mentioned previously, the utility functions of K continuous attributes follow a continuous piecewise linear function with (up to) two knots (δ_{1ik}^{B} and δ_{2ik}^{B}). This formulation is flexible enough to accommodate linear/non-linear compensatory rules, as well as non-compensatory decision rules, such as conjunctive and disjunctive rules when any of the slopes approach $+\infty$ and $-\infty$, respectively.

It is helpful to visualize these sorts of functions in order to understand what their specification "buys us" substantively. Figure 1a depicts linear compensatory rule, Figure 1b a non-linear but compensatory one. Figure 1c is a conjunctive rule where being outside of the range $(\delta_{1ik}, \delta_{2ik})$ acts as a deal-breaker, and Figure 1d is a disjunctive rule where being greater than δ_{2ik} acts as a deal-maker. The utility functions of L discrete attributes are specified by dummy variables. The model can also accommodate non-compensatory decision rules for the categorical attributes as various elements of the parameter vector γ_{il}^{B} approach $\pm\infty$. Figure 2a and 2b show a deal-breaker and deal-maker for categorical response variables.

The theoretical and empirical challenge is to distinguish deal-breakers or deal-makers from nonlinear compensatory responses. For a continuous attribute k, if any of the pairwise difference(s) among β_{1ik}^{B}, β_{2ik}^{B}, and β_{3ik}^{B} is ∞, it represents non-compensatory rule, as in Figure 1c and 1d. In reality, imposing a difference of ∞ is somewhere between meaningless and too harsh: practically speaking, if the difference is large enough to render all *other* attributes and their differences irrelevant, a nonlinear compensatory rule can function as deal-breaker or deal-maker. For example, a difference of 10 on the logit scale represents a difference in odds (and thereby probability) on the order of 20000; that is, a difference in (say, browsing) utility of -10 makes it 20000 times less likely that that person will be written to, which by any reasonable doctrinaire standards represents a deal-breaker. Similar logic can be applied to the L categorical attributes. The pairwise difference in dummy variable $\gamma_{il}^{B}s$ determines whether the attribute l functions as deal-breaker or deal-maker. [For categorical attributes, the differences need to be compared to an average, not merely to adjacent ones, since "adjacent" doesn't mean anything for purely categorical variables, e.g., ethnicity.] How big these differences should be is an important empirical question, one that we shall examine in the context of model estimates for our particular data setting.[2]

We next turn to the utility function for writing, which follows a similar general format:

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[2] That is, the researcher needs to set some pre-established (significance) level.

$$V_{ij}^{W} = \beta_{0i}^{W} + \sum_{k=1}^{K}\left[\beta_{1ik}^{W}x_{jk}^{W} + \beta_{2ik}^{W}\left(x_{jk}^{W} - \delta_{1ik}^{W}\right)_{+} + \beta_{2ik}^{W}\left(x_{jk}^{W} - \delta_{2ik}^{W}\right)_{+}\right] + \sum_{l=1}^{L}\boldsymbol{\gamma}_{il}^{W}\boldsymbol{x}_{jl}^{W}, \qquad (2)$$

$$\text{where } (y)_{+} = \begin{cases} y & \text{if } y \geq 0 \\ 0 & \text{if } y < 0 \end{cases} \text{ and } \delta_{1ik}^{W} \leq \delta_{2ik}^{W}.$$

Here, V_{ij}^{W} stands for the systematic part of the utility for user *i* of writing to user *j*. Although it follows the same specification as V_{ij}^{B}, the number of continuous and discrete attributes can of course be different from those in the browsing stage. This reflects both the empirical fact, common to all dating sites, that the information available in the browsing stage is typically supplemented by additional variables in the writing stage, and also that even information available in the browsing stage might be enhanced after one clicks to reveal a full profile.

Note that the proposed utility functions reflect interaction effects between the attributes of user *i* and those of potential mate *j.* Thus, all the attributes of potential mate *j* (x_{jk}^{B} and x_{jk}^{W}) are specified relative to user *i*'s attributes.

A Two-Stage Model of Mate Choice

Both online and offline, mate choice is explicitly a multi-stage process. Online, site users must first search for potential mates by specifying exclusion criteria based on one or more attributes, and then "browse" potential mates by looking through a list of search results and clicking on attractive profiles. Important features of mate choice behavior will be revealed at each stage. For example, a decision to restrict one's search to only members of the same race is quite different from allowing race to be just one of multiple factors determining mate attractiveness at later stages of the selection process. Similarly, offline mate searches do not consider every single person in a given region. Social networks, as well as social venues where people come into contact such as bars, workplaces, and neighborhoods mediate information about available mates. These social environments restrict who is available as a potential mate.

Figure 3 provides an overview of the choice process hypothesized in the statistical model; associated coefficients will be discussed in further detail below. The choice process consists of two stages: the search for available potential mates to consider (the decision to "browse" a particular profile), and the decision to write to a potential mate, given that his or her profile was viewed. The potential choice set includes all men or women on the dating website within the user's metro area at a given time. From these, each user views the profiles for a (typically much smaller) subset, which form the consideration set. From among the browsed profiles, the user may decide to write to one or more potential mates. At each stage, choice is governed by one or more possible decision rules. For example, users may—as implied in past research—adopt a "compensatory" approach in which they compute a weighted sum of *all* potential mates' attributes available at this stage, and browse all those profiles that fall above a user-specific acceptability threshold. Alternatively, users may impose screening rules in which they consider only those profiles that meet some threshold of acceptability on one or more attributes. For example, they may only look for mates within a narrow geographic radius, or with a given level of education or income.

Thus, compared to single stage discrete choice models used in sociology (e.g., Zeng and Xie 2008; Bruch and Mare 2006, 2013), two stage models better represent the underlying process that people are believed to use in selecting from more than a handful of alternatives. In general, decision rules trade off on effort and accuracy (Johnson and Payne 1985). In the first stage, when the goal is to reduce the number of potential alternatives to a manageable size, the decision process takes more effort due to the large number of possibilities that must be evaluated. However, the benefit of identifying the most desirable alternatives is small because there is opportunity in the second stage to more fully evaluate possibilities. In the second stage, the number of alternatives to be evaluated is much smaller (thereby reducing costs in terms of cognitive effort) and the benefit of being more accurate is greater. As a result, we expect that simpler decision rules are used in the first stage, and more comprehensive roles are used in the second stage. Note that we allow for separate decision rules at each stage, but link the two stages together using latent classes. This allows us to group different response patterns in browsing and writing together. For example, one strategy may be to restrict one's search only to a narrow age range in the browsing stage, but—among all profiles who meet the age criteria—be indifferent to potential mates' age in the writing stage.

We model each site user's behavior as a sequence of browsing and writing decisions.[3] In the first stage, the probability that the i*th* mate seeker will consider (browse)

[3] In this model, we treat the users' entire career on the site as one continuous flow of behavior; we do not distinguish among individual sessions or distinguish between choices made early in one's online dating career and choices made later on. In subsequent work, we plan to focus explicitly on the "learning" that takes place as individuals discover which potential partners are actually plausible options for them online.

the j*th* option at the t*th* time point can be written as a binary logit model:

$$p_{ijt}^{B} = \frac{\exp\left(V_{ij}^{B} - \tau_{it}^{B}\right)}{1+\exp\left(V_{ij}^{B} - \tau_{it}^{B}\right)}, \tag{1}$$

where V_{ij}^{B} is the systematic component of utility derived from browsing profile *j*, described in further detail in the next section, and τ_{it}^{B} is a threshold parameter that captures the "cost" of browsing. Intuitively, τ_{it}^{B} represents a threshold of acceptability that profiles must meet in order to justify browsing. Thus higher values of τ_{it}^{B} imply pickier site users. We can model τ_{it}^{B} as a function of the total number of messages written prior to time *t*, C_{it}, and a dispersion parameter that captures the degree to which user j is different from previously browsed profiles, D_{ijt}^{B} (Moe 2006):

$$\tau_{it}^{B} = \alpha_{0i}^{B} C_{it} + \alpha_{0i}^{B} D_{ijt}^{B}. \tag{2}$$

We expect a negative effect of C_{it} (the more potential partners already written to, the higher the costs of searching for more potential partners to write to), while the effect of D_{ijt}^{B} may vary across users based on their willingness to consider a diverse range of potential mates. Note that τ_{it}^{B} is an individual-specific, time-varying parameter and, to ensure identification, does not contain an intercept term.

In the second stage, writing behavior (conditional on browsing) is similarly specified as a binary logit model. The probability that user *i* writes to user *j* at time *t* is therefore:

$$p_{ijt}^{W} | browsing = \frac{\exp\left(V_{ij}^{W} - \tau_{it}^{W}\right)}{1+\exp\left(V_{ij}^{W} - \tau_{it}^{W}\right)}, \tag{3}$$

where V_{ij}^{W} is the systematic component of utility derived from writing to the j*th* potential mate, and τ_{it}^{W} is the threshold of acceptability for writing. Similar to the browsing stage, higher values of τ_{it}^{W} imply "pickier" users who are more selective in writing messages. We model τ_{it}^{W} as a function of the total number of messages written on the site, C_{it}, and the "dispersion" parameter capturing a taste for variability in the types of people written to, D_{ijt}^{W}:

$$\tau_{it}^{W} = \alpha_{0i}^{W} C_{it} + \alpha_{0i}^{W} D_{ijt}^{W}.$$

Note that it is not necessary that all salient attributes of potential partners be involved in both the browsing and writing stages of the model. Variables determining the composition of the consideration set and the final choice outcome may overlap partially, completely, or not at all. This reflects the empirical fact, common to all dating sites, that the information available in the browsing stage is typically supplemented by additional variables in the writing stage. It also reflects a more general fact about staged decisions making: people may have less information at early stages than at later stages. For example, in housing choice, a decision to view an apartment may be based on a subset of salient attributes: price, location, and number of bedrooms, which are supplemented by an in-person visit.

Because there are large variations in the number of profiles browsed and messages sent across users, results from a homogeneous model would differentially reflect the activities of the heaviest site users, and so we consider it especially critical to allow for so-called "unobserved" heterogeneity across users. To avoid presuming that users "clump" near some central tendency on each attribute, we use discrete heterogeneity (Kamukura and Russell 1989) or latent classes, which also benefits in identifying and interpreting distinct sorts of mate seeking strategies. Post-hoc analysis of each group can provide us with new insight of mate preference heterogeneity that cannot be captured in a homogeneous model.

Estimation

For estimation, we use the Expectation/Conditional Maximization (ECM) algorithm developed by Meng and Rubin (1993). The ECM algorithm is a variation of the Expectation/Maximization (EM) algorithm (Dempster et al. 1977), which has been commonly used for calculating MLE for latent class models (McLachlan and Peel 2004). In a mixture of regressions with changepoints, the ECM algorithm is typically used, since a single maximization step (M-step) cannot readily handle changepoints and other regression parameters simultaneously. In this case, the M-step is divided into two conditional Maximization steps (CM-steps). Most relevant to our work, Young (2012) explored mixtures of regressions with changepoint models and developed an ECM algorithm for maximum likelihood estimation. The model includes multiple predictors and changepoints in a mixture of regressions and, importantly, the number of changepoints can vary across components of the mixture. However, the resulting algorithms allow for neither data with multiple observations per individual nor for a binary response variable that is governed by a latent (unobserved) underlying continuous utility function. Therefore, we developed a new function that extends past work in two steps critical for our application setting: 1) binary response (with logit formulation), and 2) accommodating repeated measures per individual.

5. DATA

Online dating is increasingly becoming a common way to meet one's spouse. Between 1995 and 2005, there was a rapid increase in the number of heterosexual couples who met their partners online (Rosenfeld and Thomas 2011). A study commissioned by Match.com in 2010 reported that 1 in 6 couples married within the past three years met their partner on an online dating site, and 1 in 5 people have dated someone they met on an online dating site (Chadwick 2010). After conditioning on Internet use, Sautter and colleagues found that approximately one third of all people who had been single at some point over the previous ten years had used Internet dating websites (Sautter, Tippett, and Morgan 2010). Some individuals are more likely to use online dating sites than others. Rosenfeld and Thomas (2011) report that the people most likely to use online dating sites are those operating in a thin market, for example, gays, lesbians, and middle-aged heterosexuals. These are the populations who stand most to benefit from the market efficiencies in online dating. The expansion in online dating correlates with an increase in Americans' Internet use. According to Current Population Survey data, 55 percent of all households had Internet access; this is more than triple the proportion of the population with Internet access in 1997 (Day, Janus, and Davis 2005). However, some social groups are more likely to have Internet at home than others. Being white, highly educated, high income, and/or having a school-aged child in the household are all positive predictors of Internet use.

There are several advantages to using online dating data to study mate choice. First, since we know who is active on the site at any given time, the choice set can be observed and explicitly represented for all members of the site. Second, all overtures are observed regardless of whether or not they are reciprocated. Third, because all members of the site are theoretically just a click away, the online dating environment in theory represents a frictionless environment. (After all, the whole purpose of online dating is to reduce search costs in the marriage and dating market.) A potential disadvantage of online data, of course, is that we do not observe if two users who met online actually date, cohabit, or marry. Given that more homogamous matches tend to persist over time, we would expect that the preferences estimated from online dating data would imply more heterogamous matches than what prevailing marriages would suggest (Schwartz 2010). Overall, these data should be viewed as representing preferences at an early stage of mate selection. It is likely that preferences for more superficial attributes (attractiveness or human capital) are most salient in the early stages of mate choice, when people have had less opportunity to bond on more idiosyncratic traits or personality.

This study estimates mate preferences from observed activity on a popular online dating website. The data were originally analyzed by Hitsch, Hortaçsu, and Ariely (2010) using a single-stage, homogenous, compensatory response logit model. The sample includes all users active in the San Diego and Boston metro areas over a six-month period. We restrict our sample to users who are 1) heterosexual; 2) single, divorced, or "hopeful"; 3) "looking for a long term relationship", "just looking", "making friends", or claimed that a "friend put my up to this"; and 4) within the ages of 18-65. We also eliminate any user who failed to browse any profiles. This provides 10,271 users in total. There are roughly equal numbers of men (52.5%) and women (47.5%) and about equal numbers of users from Boston (48.2%) and San Diego (51.8%).

Process of Searching for a Mate Online

When they join a dating service, users must fill out a profile providing answers to a number of survey questions as well as several short answer essays. These include measures of a range of demographic attributes (income, marital status, whether they have children, education, race, religion, and age) as well as measures of cultural interests, whether they attend church frequently, spending habits and expectations for a first date. Users are also asked to indicate whether they would be willing to travel to meet a mate, and whether race and religion are important for them in evaluating potential mates. Many users also include one or more photos in their profile. Once they have completed their profile, users can search for, browse, and write to potential partners. Users typically begin by searching for mates based on a specified age range and geographic region. This query returns a list of "short profiles" containing information on potential partners' age, user name, a brief description, and a photo if available. Users can then decide to "browse" potential mates by clicking on their short profile to access the complete profile containing the full set of profile attributes as well as essay questions, larger versions of the main photo, and additional photos if available. Based on the full profile, users can then decide to write to a potential mate. The data provided a complete moment-by-moment description of users' activities, including which profiles he or she browsed, whether or not the photos were viewed, and whether the user sent a first contact message.

Thus, the site generates two types of data: 1) user registration information (i.e., profiles), and 2) activities observed on the site. The user registration data contain a variety of attributes, including users' age, education, race/ethnicity, education, income, height, weight, and self-rated attractiveness. Our preliminary analysis focuses on two continuous attributes: height and age, as well as three discrete attributes: race/ethnicity, having children (or not), and education level. Because we suspect that mate seekers evaluate many attributes of potential mates relative to their own value, most of these variables are entered into the model as interactions with one's own value level.

Table 1 lists the attributes used in the analysis taken from the user registration data. We see that, on average, men on the site are five inches taller than women on the site, and both male and female site users are, again on average, in their late thirties. As mentioned previously, to identify deal-breakers/makers, we focus on differences in age and height between the users.[4] More than 80 percent of users are white, and less than 5 percent are black. About 38 percent of female users and about 42 percent of male users have children. We examine interactions between users with kids (K) and users without kids (NK) to see whether men and women only consider potential partners who share their family status. Finally, users on the site span the full range of education, ranging from less than high school to a doctoral degree. We partitioned the thirteen categories of education into three categories: 1) Lower (L) which means less than college degree; 2) College (C) which means college degree; and Advanced (A) which means post-college degree. Users currently enrolled in school (high school, college, graduate school) are dropped because the degree of social friction and income might be different from other users. In the analysis, we use eight dummy variables for the interaction effects to examine how education level affects mate choice. While these data are not strongly representative of the Boston and San Diego adult populations, they are roughly representative of Internet users in those areas (Hitsch, Hortaçsu, and Ariely 2010, p. 137).

[4] We assume that what matters to mate seekers is the distance between the potential partner's attribute value and their own attribute value, rather than the absolute value of potential partners' attribute values. For example, a woman does not care how short a man is as long as he is at least two inches taller than her. Contrast this with a woman who refuses to date a man under 5'5", regardless of her own height. In actuality, people probably evaluate potential mates' attributes in both absolute and relative terms.

Table 2 shows activity data for male and female users. The table is divided into "active" (browsing, sending a message) and "passive" (being browsed, receiving a message) activities on the site. These tables show that male users do far more browsing and writing than female users. Male users browsed and sent messages at more than double the volume of female users (active). Conversely, female users were browsed and received far more messages than male users (passive).[5]

6. RESULTS

TO BE ADDED.

7. REFERENCES

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[5] One might argue that, since women send far fewer messages than men, the bulk of their mate choice behavior occurs in their decisions to reply (or not) to messages. However, the vast majority of women on the site do send at least one contact message during their online dating careers, suggesting that these data do carry important information on women's mate choice behavior. Moreover, analyses of reply rates are difficult to interpret as the rate likely depends on the volume of messages one receives. Moreover, replies are conditional on receiving a message in the first place. Thus, we focus here on initial first contacts.

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Table 1. User Attributes from Registration Data

	Men	Women
Height (inches)	71.5	65.5
Age	38	38
Race (%)		
White	85	85
Black	3	3
Hispanic	5	5
Asian	3	3
Has Kids (%)	38	43
Education		
Less than College	15	12
College Graduate	56	58
Advanced Degree	29	30

Table 2. Browsing and Writing Behaviors for Male and Female Users

A) Male Users

Active	Browsing	Total browsing hits	566,374					
		Male users who browsed	5,233 (83.1%)					
		Browsing hits per user	mean	min	Q1	median	Q3	max
			108.23	1	14	45	135	1,396
	Writing	Total messages sent	57,338					
		Male users who wrote	3,184 (50.6%)					
		Messages sent per user	mean	min	Q1	median	Q3	max
			18.01	1	2	4	14	581
Passive	Getting browsed	Female users who got browsed	5,851 (100%)					
		Browsing hits per user	mean	min	Q1	median	Q3	max
			96.80	1	14	32	134	979
	Receiving a message	Female users who received messages	4,693 (80.2%)					
		Messages received per user	mean	min	Q1	median	Q3	max
			12.22	1	2	6	15	144

B) Female Users

Active	Browsing	Total browsing hits	257,242					
		Female users who browsed	4765 (81.4%)					
		Browsing hits per user	mean	min	Q1	median	Q3	max
			53.99	1	9	27	67	1,294
	Writing	Total messages sent	15,078					
		Female users who wrote	2,391 (40.9%)					
		Messages sent per user	mean	min	Q1	median	Q3	max
			6.31	1	1	3	6	120
Passive	Getting browsed	Male users who got browsed	6,297 (100%)					
		Browsing hits per user	mean	min	Q1	median	Q3	max
			40.85	1	4	12	50	805
	Receiving a message	Male users who received messages	2,985 (47.4%)					
		Messages received per user	mean	min	Q1	median	Q3	max
			5.05	1	1	3	6	65

Figure 1: Decision rules for continuous (ordinal) attributes

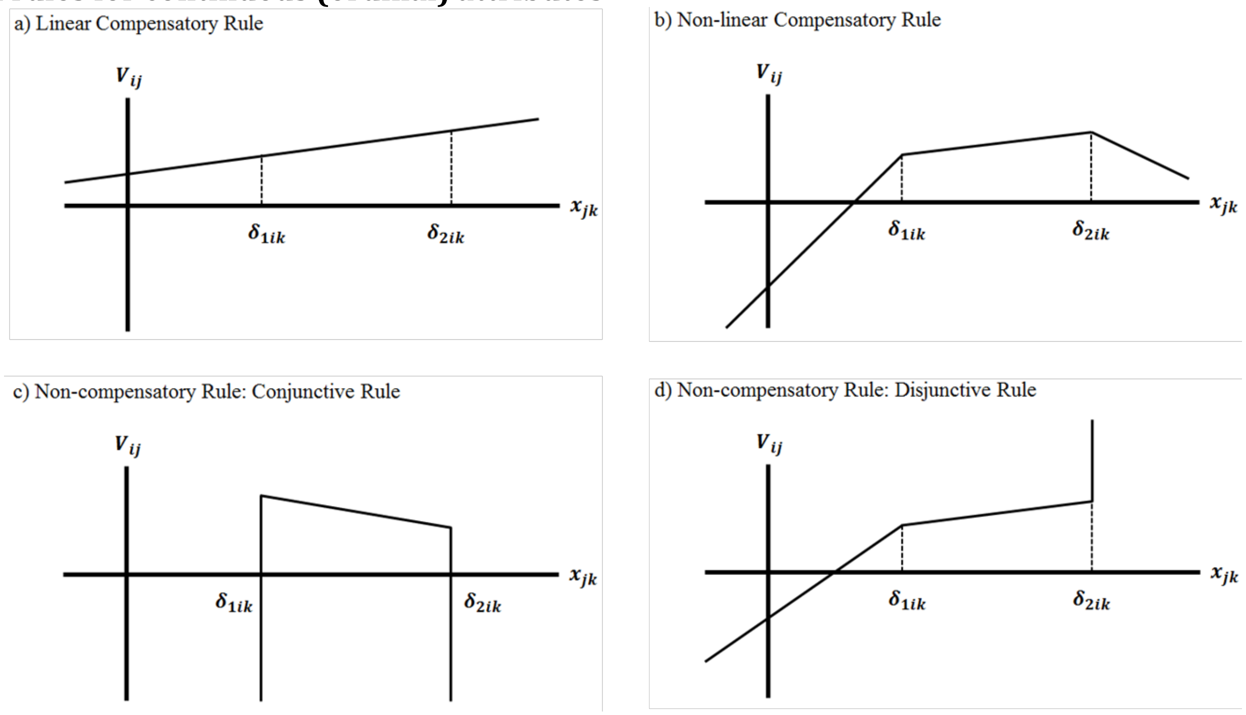

Figure 2: Decision rules for categorical attributes

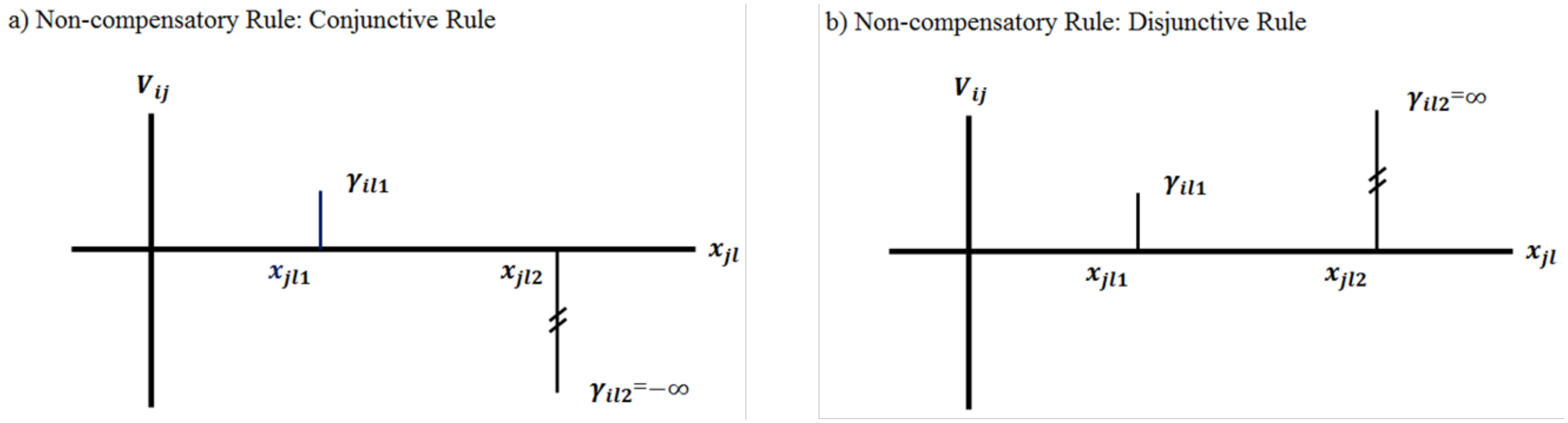

Figure 3: Diagram of Mate Choice Process