Estimating Preferences In Two-sided Matching markets

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ABSTRACT

In two-sided matching markets –such as labor markets– the outcome is a function of agents' preferences. If we could infer preferences from market outcomes, we could advise market agents on how to improve their odds of matching with a desirable partner. We introduce a model to estimate agents' preferences and consideration sets in two-sided matching markets and illustrate its use with data from the marketing assistant professor job market. Our results show that asymmetry of preferences is common. For example, a marketing department may be effective in getting its graduates good placements but may be less attractive as a hiring department. University ranking is a significant factor –but not the most critical– in determining the appeal of the university as a hiring institution as well as the university's graduates. The most critical factor for candidates is publication in a select few top journals, while for hiring departments it is the establishment of a Ph.D. program. Finally, our estimates explain market outcomes well, in addition to eigenvector centralities, implying that our preference estimates capture valuable additional information from the structure of two-sided matching markets.

Keywords: Two-sided matching; marketing job market; labor markets; consideration sets; social networks.

1. INTRODUCTION

Two-sided matching markets are the earliest form of social interaction and predate bartering and commercialization, as they are the natural outcome of evolutionary forces (Miller 2001). Yet the recognition of matching considerations has gained in popularity only recently with the advent of a plethora of networked platforms for dating, job search, online gaming and crowdsourcing. Monetization opportunities have ensued: the executive search industry was valued at $11bn by the Association of Executive Search Consultants as of 2008, and the online dating industry is currently valued at $4bn (The Economist, 2010).

In two-sided matching markets, market participants (hereafter agents) belong to one of two sides,[1] and their objective is to partner or "match" with an agent on the other side (Roth and Sotomayor 1990). Unlike markets where agents exchange goods, agents themselves may be thought of as the object of exchange.

A common primitive that underlies two-sided matching markets is the willful exercise of choice. Agents carefully weigh their own preferences, their potential partners' preferences, and their rivals' preferences to determine which set of partners they should "market themselves" to in the hopes of matching with one of them. Therefore, exchanges in matching markets are facilitated to the degree that one is appealing, or, analogously, more preferred: NBA players and teams wish to match with prospects conducive to increase their brand value (Yang, Shi, and Goldfarb 2009); firms would prefer partners with strong brands, as these enjoy added control over distribution networks (Keller and Lehmann 2006); universities leverage on their prestige to

[1] A match in a two-sided matching market is in many respects similar to an undirected tie between actors in a social network (Christakis et al. 2010), where market sides need not exist. The current framework may be extended to more general settings, and we will discuss this in the last section.

court top job candidates (Zamudio, Wang and Haruvy 2013), who also strive to be hired by prestigious universities to further their scholarly careers (Bedeian et al. 2010).

Establishing the importance of individual preferences in two-sided matching markets is trivial, but going about estimating them is a more involved task. Because agents' preferences all simultaneously enter the choice problem, they are hard to disentangle (Fox 2010). The matter complicates because agents can potentially choose among hundreds of partners, and consideration set effects could exist. Most importantly, choices in two-sided matching markets do not fully reveal individual preferences, for a match informs of agents' "best possible" partners in the face of rivalry, not of agents' most preferred partners.

Solutions to overcome the above limitations exist to some extent. In the two-sided matching markets literature, the estimation of joint utility has been proposed in lieu of individual level preferences (e.g. Yang, Shi, and Goldfarb 2009). Using the joint utility approach leaves the researcher unable to estimate individual preferences –how much value each agent derives from a match cannot be separately identified under most conditions (Fox 2010). Therefore, balances (or imbalances) of value sharing among partners, and their ulterior effects on market outcomes, cannot be determined.

Recent work (Hitsch, Hortaçsu and Ariely 2010a, b) circumvents the revealed preference limitation by using exogenous data on private preferences. Yet in most situations researchers may not have access to the large amounts of exogenous data required. Our approach differs from the work of these authors in that we focus on estimating a single preference metric which requires less data.

Our contribution is to develop a comprehensive model of preferences in two-sided matching markets that emphasizes data economy. The goal is to estimate preference metrics to parsimoniously describe the desirability of an agent in a two-sided matching market. To this end, our model estimates the individual preferences and consideration sets of agents in two-sided matching markets, and requires only a minimum of two periods of match data. Covariates allow the determinants of individual preferences to be investigated as well, but they are not required to estimate preferences.

Using our model, we discover that agents can be preferred differently depending on which task they perform in a two-sided matching market. The model allows us to gauge precisely how different these preferences are. We also find that individual preference estimates explain matching market outcomes well. We compare our preference metric to eigenvector centrality, a social network metric used to measure agent influence. Interestingly, both our preference estimates and eigenvector centralities have a significant effect on predicting market outcomes. This suggests that our preference metrics complement the use of centrality metrics in explaining market outcomes. The above results stem from applying our model to the matching data from the marketing job market.

We proceed as follows. Section 2 sets up the research background of the present work. Section 3 develops our preference model. Section 4 applies our model to the matching data from the marketing job market and reports preference estimates and their determinants. Section 5 compares our preference estimates with eigenvector centrality.

2. RESEARCH BACKGROUND

Approaches to investigate preferences in two-sided matching markets (hereafter referred to as "matching markets") fall under two broad research streams. The first one focuses on estimating joint utilities. We refer to this as the joint utility stream. The second one consists of estimating matching preferences with social networks models that use influence metrics as opposed to preference metrics. We refer to this as the social network stream.

The joint utility stream relies on the assumption that *any two* observed matches produce the maximum joint utilities that involve the four agents in these matches. This is derived from the underlying concept that, in equilibrium, any agent has received the best possible outcome given his own preferences and those of others. This equilibrium concept permits identification of the joint production value of any two agents. Zamudio, Wang and Haruvy (2013) employ this methodology to investigate the marketing job market and find complementarities between marketing scholars in different fields (CB/Modeling/Strategy). They also find that the value of journal articles is moderated by candidates' ranking status. Using the same methodology, Yang, Shi and Goldfarb (2009) examine the NBA free agent market and find that matches between high brand equity players and medium brand equity teams generate the highest joint utility. Fox (2010) investigates the automobile parts market and finds that US suppliers to foreign car assemblers are of higher quality than those that do not supply to foreign assemblers. A disadvantage of the joint utility approach is that the joint production value cannot be disentangled except for many-to-many matching markets (Fox 2010). Furthermore, consideration set effects are absent from these models.

The social network stream is concerned with measuring the impact of social influence on marketing outcomes (Van den Bulte and Lilien 2001; Nam, Manchanda, and Chintagunta 2006; Bell and Song 2007; Nair, Manchanda, and Bhatia 2010; Trusov, Bodapati and Bucklin 2010; Iyengar, Van den Bulte and Valente 2011; Ansari, Koenigsberg, and Stahl, 2011). To measure social influence, most researchers calculate centrality metrics for each agent. The implicit assumption is that central agents should be most influential and, as a result, most preferred, with some exceptions (e.g. Gelper, van der Lans and van Bruggen 2013). Consequently, the degree to which influence and preference overlap is an open question. Furthermore, agents who participate less in matching markets are thought of as less central - despite the fact that this low participation may be due to exclusivity. Consideration set effects are also absent in this stream of research.

While the novel methodologies employed in both research streams provide useful characterizations of matching markets, the model we present in this paper highlights (1) how preferred each agent is can be summarized using a single metric; (2) agent participation in the market (i.e. each agent's scarcity) should influence the estimation of these preferences; and (3) consideration set effects must be introduced into the preference model.

In particular, we do the following. First, we identify the individual contribution of each agent in a pair. This means that for each match in the market, our model produces a separate preference metric for each agent. We study the marketing job market as our empirical application, where each agent participates as a “placing department” that trains and places Ph.D. students on the market, as well as a “hiring department” where those students are placed. Therefore, the model produces the schools’ preference metrics separately for each of these two roles. Second, we allow preference estimates to be influenced by scarcity by placing an exogenous weight on the utility each agent provides to the other. This exogenous weight is a function of market participation. Third, we explicitly model the formation of consideration sets in matching markets. These are endogenously estimated using data on past matches.

Incorporating consideration sets into the model is critical. First, methodologically, it is known that ignoring consideration set formation can lead to biased estimates in various settings (e.g., Abramson et al. 2000). Yet the implicit assumption in extant works on matching is that agents consider all other possible agents for matching. Second, theoretically, it is known that agents of similar qualities tend to match more frequently with each other because of positive assortative matching (Becker 1973) or homophily (Lazarsfeld and Merton 1954). This has also been verified empirically (Hitsch, Hortaçsu and Ariely 2010a, b).

However, estimating consideration sets in matching markets is complicated because, quite often, many agents participate in these markets. Degrees of freedom may not be sufficient to estimate a separate metric (intercept) for each agent. To alleviate this problem, we introduce the "focal agents" assumption. For each side of the market, a subset of agents, which we call focal, is chosen for estimation. In a sense, the focal agents assumption is present in most consumer choice studies as well. For example, in grocery studies, a number of national brands are chosen as the object of study and other brands are collapsed into a benchmark. As in consumer choice models, this assumption implies that benchmark agents share the same preference coefficient, set to zero, as well as the same estimated consideration set. Yet unlike consumer choice models, the focal agents assumption poses a special limitation: it implies that transacting with benchmark agents is perceived negatively by the focal agents –"inbreeding" is preferred to "cross-breeding." This means that birds of a feather indeed flock together in the current specification (Becker 1973; Lazarsfeld and Merton 1954). In markets where this is unclear, the focal agents may need to be specified using other arguments.

Selecting a subset of focal agents for estimation is idiosyncratic to the market under examination. For example, in the executive job search market, the *Fortune 100 Best Companies to Work For* could be set as focal and other companies set as benchmark. Alternatively one may use transactional data outside of the matching process to determine which agents transact more heavily with others. With enough degrees of freedom, the focal agents assumption can be relaxed and individual preferences for every agent in the market can be estimated.

3. A PREFERENCE MODEL FOR MATCHING MARKETS

Choices in matching markets involve interrelated preferences. Consider a two-sided matching market with sides denoted set C and set D. On one side of the market, each agent c_i belongs to set $C = \{c_1, \dots, c_n\}$. On the other side of the market, each agent d_j belongs to set $D = \{d_1, \dots, d_m\}$. Note that not all agents may be present [2] in every time period $t = 1, \dots, T$. Consequently, let $\delta_{c_i t}$ and $\delta_{d_j t}$ take the value of 1 if c_i and d_j, respectively, were present in the market at time t, and 0 otherwise. Agents' characteristics may vary across periods and are represented by X_c = $\{x_{c_{1t}}, \dots, x_{c_{nt}}\}$ for agents in set C and X_d = $\{x_{d_{1t}}, \dots, x_{d_{nt}}\}$ for agents in set D.

Agent c_i's preference for agent d_j at time t is denoted by $x_{d_j t}\beta_{d_j}$, where $x_{d_j t}$ are agent d_j's characteristics at time t and β_{d_j} defines the mapping between the characteristics of d_j and the utility for agent c_i from selecting d_j. In other words, β_{d_j} captures how appealing d_j's characteristics are from the standpoint of c_i.

For agent c_i, the acceptable consideration set at time t is $D_{c_i t} \subseteq D$. Similarly, for agent d_j on the opposite side, the acceptable consideration set at time t is $C_{d_j t} \subseteq C$. Note that if any c_i or d_j is not present in the market during period t, then $\delta_{c_i t}$ and $\delta_{d_j t}$ for these agents equal zero, and neither can belong to any acceptable consideration set.

[2] We make the assumption that being unmatched is equivalent to being absent from the market, as opposed to being in the market and failing to find an acceptable partner.

Each agent must find a match from his acceptable consideration set that maximizes his or her utility. Consequently, at time t, c_i solves $max_{d_j \epsilon D_{c_i t}} \mathcal{U}_{c_i d_j t}(x_{d_j t} \beta_{d_j})$ and d_j solves $max_{c_i \epsilon C_{d_j t}} \mathcal{U}_{d_j c_i t}(x_{c_i t} \beta_{c_i})$. The above suggests that the probability that c_i considers d_j during period t as his utility-maximizing choice depends on two factors: the utility that c_i can obtain from d_j at time t, and the composition of c_i's acceptable consideration set D_{c_i} at time t. The converse holds true for d_j. For these reasons, one would expect the probability that a match between c_i and d_j is observed at time t to be influenced by the same factors as well.

Aside from market agents' preferences, matching can be restricted by the lack of availability of some agents, as indicated by $\delta_{c_i t}$ and $\delta_{d_j t}$. This highlights the necessity to incorporate consideration sets into preference estimation in matching markets. Market outcomes are observed in the form of matches between pairs of market agents for each time period. Fig. 1 shows how preferences for market agents enter the utility functions of each agent in matching markets.

Insert Figure 1 about here

We now turn to developing a model to estimate agents' preferences in matching markets, along with their consideration sets. Our approach accommodates the particular conditions under which choices in matching markets occur as discussed earlier. Fig. 2 shows an overview of our framework.

Insert Figure 2 about here

The model consists of three steps. In the first step, the researcher must decide which agents will have their preference parameters estimated and which agents will be subsumed into a benchmark option, as in consumer choice models. In the second step, individual preferences and consideration sets are estimated using match data alone. Stated consideration sets can be used if the researcher has access to them; otherwise, they are endogenous. In the third step, the determinants of preferences are estimated using a linear model.

3.2. Individual Preference Model

Our model produces individual preference estimates for the focal agents on each side of a matching market by specifying a Logit probability model that accounts for agent scarcity and by incorporating consideration set estimation. We only require matches for more than one period. No equilibrium assumptions are made regarding the matching configuration observed.

To lay the foundations of our model, assume subscripts c_i and d_j are interchangeable. The characteristics of the matched agents, $x_{c_i t}$ and $x_{d_j t}$, include only intercepts, and thus $x_{c_i t} = \delta_{c_i t}$ and $x_{d_j t} = \delta_{d_j t}$. Then, the utility that any agent c_i obtains when matched with any agent d_j at time t can be expressed as

$$U_{c_i d_j t} = \beta_{d_j} + \varepsilon_{c_i d_j t} \tag{1}$$

where $\varepsilon_{c_i d_j t}$ and $\varepsilon_{d_j c_i t}$ are i.i.d. extreme-value distributed for all c_i, d_j following Christakis et al. (2010). The coefficients $\beta = \left\{\beta_{c_i}, \beta_{d_j}\right\}$ represent how preferred each agent is, and do not vary across periods, agents, or markets. The preferences of all benchmark agents are set to zero for identification. If there are no clear market sides in the matching market (such as in a social network), then β contains only one vector of parameters for all agents in the market.

Each observed match at time t features a pair of agents, c_i and d_j, which match with probability $P_t(c_i \rightleftarrows d_j)$. This probability depends on c_i's preferences for d_j and *vice versa*. The probability that a match between c_i and d_j is observed at time t can then be expressed as

$$P_t(c_i \rightleftarrows d_j) = P_t(c_i \longrightarrow d_j) * P_t(d_j \longrightarrow c_i) \tag{2}$$

which stems from the independence between $\varepsilon_{c_i d_j}$ and $\varepsilon_{d_j c_i}$. Here, the expression "$c_i \rightleftarrows d_j$" means "c_i matches with d_j" and the expression "$c_i \longrightarrow d_j$" means "c_i prefers d_j over all other agents." Eq. 2 captures the notion that an observed match has to be mutually appealing for both parties. For simplicity, assume n and m refer only to market agents observed at time t. Then, the probability $P_t(c_i \longrightarrow d_j)$ can be specified as

$$P_t(c_i \longrightarrow d_j) = P_t\left(U_{c_i d_j t} \geq U_{c_i d_1 t}, \ldots, U_{c_i d_j t} \geq U_{c_i d_m t}\right) = \frac{\sum_{q_{d_j t=1}}^{Q_{d_j t}} e^{\beta_{d_j}}}{\sum_{z_j \in D} \sum_{q_{z_j t=1}}^{Q_{z_j t}} e^{\beta_{z_j}}} \tag{3}$$

where $D_{c_i t}$ represents agent c_i's consideration set, which at this point includes all agents present in the market at time t, i.e. those for whom $\delta_{d_j t} = 1$. Eq. 3 is a variation of the Logit form, where $q_{d_j t} = 1, \ldots, Q_{d_j t}$ denotes the number of times d_j participated in the market at time t. The functional form of Eq. 3 is needed because subsuming many agents into a single benchmark agent implies that it will vastly outnumber the focal agents. Since in an intercept-only Logit the probability of choice is higher when an alternative is chosen many times, lower preference estimates for the focal agents would result because they are scarce and, thus, chosen less often.

Hence, the functional form in Eq. 3 compares agents' preference estimates *after* accounting for the relative difference in their market activity.[3]

Screening rules. The probabilities $P_t(c_i \longrightarrow d_j)$ and $P_t(d_j \longrightarrow c_i)$ currently capture the preferences of agents without considering the preferences of other agents. The only restriction is via the consideration set $D_{c_i t}$. We incorporate these preferences onto the match probabilities placing a further restriction on $D_{c_i t}$ by modeling how agents form their consideration sets.

The number of alternatives in matching markets is typically large. Thus, the conventional approach to model consideration sets (e.g. Andrews and Srinivasan 1995; Mehta, Rajiv and Srinivasan 2003) leads to a curse of dimensionality because the approach requires to uncondition probabilities of choice over $2^k - 1$ possible true consideration sets (Chiang, Chib and Narasimhan 1999), where k is the number of alternatives available. In our empirical application, this requires unconditioning over up to at least 1,099,511,627,775 possible true sets on each side of the market, respectively, which is computationally burdensome. An approach that solves this problem is to model consideration sets as the outcome of inequalities (van Nierop et al. 2010) or screening rules (Gilbride and Allenby 2004). We rely on these ideas to incorporate consideration sets into our specification. For agent c_i, screening rules $\Phi^t_{c_i d_j t}$ enter the probabilities in Eq. 4 as constraints to form his or her acceptable consideration set as shown:

$$P_t(c_i \longrightarrow d_j) = P_t\left[U_{c_i d_j t} \geq \left(U_{c_i d_1 t} * \Phi_{c_i d_1 t}\right), \ldots, U_{c_i d_j t} \geq \left(U_{c_i d_m t} * \Phi_{c_i d_m t}\right)\right] \quad (4)$$

[3] As will be shown in Section 4, the specified functional form does not imply that "the more an agent matches, the worse its preference estimate" or the converse. In fact, there is no statistically significant relation between number of matches and preference estimates in our empirical application.

The behavioral underpinnings of screening rules $\Phi_{c_i d_j t}$ operate as follows. Suppose agent c_i is assessing which agents among all agents in $D_{c_i t}$ to potentially match with at time t. c_i is assumed to know the identity of every agent in $D_{c_i t}$ and their history of matches in the past up to time t, denoted as $H_{D_{c_i t} v}$. Here v denotes the number of periods c_i looks into the past to assess d_j's past performance; furthermore, v is assumed to be invariant across all time periods under investigation. Let this assessment be

$$A_{c_i d_j t} = median\left(\beta_{H_{D_{c_i t} v}}\right) \tag{5}$$

In other words, because c_i knows d_j's history, and β does not vary across time, c_i knows how appealing the agents with whom d_j matched were in the past and can use this information to form assessment $A_{c_i d_j t}$. This assessment varies by period because new matches are observed over time. If v is low, new matches replace old information, and if $v = \infty$, new matches complement old information. Note that other ways of computing $A_{c_i d_j t}$, such as the mean, can also be used.

The assessment $A_{c_i d_j t}$ allows c_i to decide whether to target agent d_j as follows. c_i is assumed to believe d_j will consider agents that "have a shot" at it: this occurs if $\beta_{c_i} \geq A_{c_i d_j t}$. If this condition holds, d_j is targeted. However, even if $\beta_{c_i} < A_{c_i d_j t}$, c_i may believe there is still opportunity to consider d_j, for even if c_i is not attractive enough, d_j may not screen c_i out unless $\beta_{d_j} > A_{d_j c_i t}$. In other words, even if c_i would screen d_j out, d_j may not, and vice versa. Thus, both conditions $\beta_c < A_{c_i d_j t}$ and $\beta_{d_j} > A_{d_j c_i t}$ must be satisfied for agent c_i to screen out d_j. Formally, c_i's screening rule is

$$\Phi_{c_i d_j t} \begin{cases} 0 \text{ if } \beta_{c_i} < A_{c_i d_j t} \; and \; \beta_{d_j} > A_{d_j c_i t} \text{ (screen)} \\ \qquad 1 \text{ otherwise (target)} \end{cases} \tag{6}$$

Because two conditions must hold for screening to occur, the screening conditions are not too harsh; in any case, the incidence of screening can be assessed empirically. Screening rules $\Phi_{c_i d_j t}$ ensure that each agent faces a potentially unique consideration set. The formation of these sets depends on agents' past behavior in the market and how appealing rival and alternative agents are. Mathematically, if choosing agent c_i screens agent d_j, then the utility that agent d_j provides to agent c_i will be $U_{c_i d_j t} * \Phi_{c_i d_j t} = U_{c_i d_j t} * 0 = 0$ since screening d_j implies $\Phi_{c_i d_j t} = 0$. Thus, when exponentiated, the utility that c_i derives from d_j equals the benchmark agent's preference parameter in the market. Note, finally, that if consideration set data is available, screening rules are not required. When some, but not all consideration sets in a dataset are available, these can be incorporated and the rest can be estimated. As will be shown in Section 4, even limited consideration set data significantly improves model fit.

After screening, $D_{c_i t}$ now contains c_i's acceptable consideration set. Similarly, $C_{d_j t}$ now contains d_j's acceptable consideration set as well. Again, for simplicity, assume n and m refer only to market agents included in the acceptable consideration sets of c_i and d_j, respectively, at time t The probability specification then becomes

$$P_t(c_i \longrightarrow d_j) = P_t\left[U_{c_i d_j t} \geq \left(U_{c_i d_1 t} * \Phi_{c_i d_1 t}\right), \ldots, U_{c_i d_j t} \geq \left(U_{c_i d_m t} * \Phi_{c_i d_m t}\right)\right]$$

$$= \frac{\sum_{q_{d_j=1}}^{Q_{d_j}} e^{\beta_{d_j}}}{\sum_{z_j \in D_i} \sum_{q_{z_j=1}}^{Q_{z_j}} e^{\beta_{z_j}}} \tag{7}$$

The parameters that maximize $P_t(c_i \rightleftarrows d_j)$ across all time periods must be estimated. Denote $M_t(c_i, d_j)$ as an indicator which equals 1 if c_i matches with d_j during time period t and 0 otherwise. The log-likelihood for this model can then be specified as

$$L(\beta) = \sum_t \sum_{ij} M_t(c_i, d_j) \ * P_t(c_i \rightleftarrows d_j) \tag{8}$$

By maximizing $L(\beta)$ we can obtain preference estimates $\hat{\beta}$ and, for all focal agents and time periods, we also obtain their estimated acceptable choice sets $\hat{C}_{d_j t}$ and $\widehat{D}_{c_i t}$.

3.3. Preference Regression

The determinants of preferences can be assessed once the parameters $\hat{\beta}$ are estimated. To this end, one can regress the estimated preference parameters $\hat{\beta}$ on agent characteristics. This yields a set of estimates $\hat{\gamma}$ that quantify the contribution of each characteristic to agents' preferences.

3.4. Estimation of Individual Preference Model

Different values of the parameter vector β potentially change the consideration set of each agent because the screening rules $\Phi_{c_i d_j t}$ cause the limits of integration of $P_t(c_i \longrightarrow d_j)$ and $P_t(d_j \longrightarrow c_i)$ to change at every step of the optimization routine (Gilbride and Allenby 2004). In consequence, the optimization routine will find new values that maximize the likelihood abruptly instead of smoothly, and the surface of the likelihood function will be irregular. Hence, if gradient optimization is used, a local maximum will be reached. Gilbride and Allenby (2004) use Bayesian estimation to deal with the irregularity of the likelihood function. This paper introduces a simple, alternative approach that relies on global optimization and gradient optimization methods jointly.

Consider that the parameters that optimize the likelihood function may be found using a global optimization method, since these methods are robust to local optima. Global optimization, however, will yield point estimates at the global maximum, but no standard errors. These could be bootstrapped at the cost of burdensome computation. But since our model is parametric, it would be desirable to compute standard errors directly from an estimated Hessian matrix.

With the above in mind, the parameters that maximize the likelihood are estimated using the Differential Evolution (Storn and Price 1997) global optimization method. This yields global point estimates $\hat{\beta}$. Next, the estimates $\hat{\beta}$ are used as starting values on the same likelihood function using gradient optimization. The optimization routine converges immediately and yields an estimated Hessian from which the standard errors of the resulting parameters may be computed.

The estimation approach discussed above conveys several advantages. First, the global maximum of the likelihood function is likely to be reached (Storn and Price 1997). Second, familiar gradient methods can be utilized straightforwardly. This is advantageous for computational and expositional purposes.

3.5. Identification of Individual Preference Model

Apart from the focal agents assumption, our preference model has few requirements for identification. Because the model requires historical data on each agent's matches, multiple periods are required. For very thick markets, one period into the past may suffice; for thinner markets in which agents do not participate every year, more periods may be needed. This is similar to choice models that use exogenous data (such as past choices) to build agents' consideration sets or to inform choice estimates (e.g. Mehta, Rajiv and Srinivasan 2003).

The critical element for identification in our model is enough variation in agents' matching patterns. Because we rely on match data alone to infer preferences, it is differences in (1) the matching patterns of agents in the market and (2) the number of times each agent matched in the market, relative to each other, that inform of agents' quality.

Consider a fictitious academic job market in which agents in either side of the market can be divided into types $p = 1, \dots, 6$. These types denote an agents' quality, such that $p = 1 > p = 2 > \cdots > p = 6$. Consequently, one would expect $p = 1$ to be scarce and of high quality as compared to the P^{th} group, which represents the benchmark agent. Fig. 3 illustrates two possible empirical distributions of matches for two hypothetical departments D_A and D_B in this market.

Insert Figure 3 about here

On both panels of Fig. 3, the Y-axis represents the relative frequency of matches for departments D_A and D_B. This relative frequency varies because D_A and D_B can match with agents of many types such that if D_A matched exclusively with Type 1 agents, then $(\mathrm{Y}|p = 1) = 1$; if half of D_A's hires are Type 1 and half are Type 2, then $(\mathrm{Y}|p = 1) = .5$, $(\mathrm{Y}|p = 2) = .5$, and so forth. We show two sets of empirical matching distributions: Panel 1 depicts the scenario where D_A matched with higher quality types as opposed to D_B, and Panel 2 depicts a scenario where both agents matched with other agents of comparable quality.

In Panel 1, D_A and D_B participated an equal number of times in the market ($N_A = N_B = 100$). Because D_A matched primarily with agents of Type 1, one would expect the quality of D_A to be superior to that of D_B. But in the case of Panel 2, which agent is of better quality is unclear because the relative frequencies of matches are almost identical. In such a case, the scarcity of D_A and D_B can provide additional information on which agent is better. Although the relative distribution of matches across agent types is similar for D_A and D_B, here D_B heavily participated in the market ($N_B = 150$) as compared to D_A ($N_A = 50$). One can then infer that D_B is less exclusive and thus less valuable. Hence, both the difference in matching patterns and the number of matches in the market per agent can inform of the quality of agents using match data alone.

4. EMPIRICAL APPLICATION

In this section we apply our preference model to data from the marketing job market. We first estimate preferences for a set of marketing departments and then (1) assess the extent to which preferences are different in the placing and hiring functions; (2) investigate the determinants of marketing department preferences; and (3) compare the effect of our preference estimates with eigenvector centrality metrics. We use two datasets to this end. The first dataset consists of a large number of matches from the marketing job market. The second dataset consists of a survey of stated consideration sets for a subset of the matched agents in the first dataset.

Matching dataset: We assembled a large dataset of matches between job candidates and hiring marketing departments in the marketing job market. The matching dataset consists of 1,149 matches between job candidates from 125 placing Marketing departments and 388 hiring Marketing departments that took place during the 1997-2009 period. We include information on candidates' publications, ranking status, and field of research, as well as hiring departments' ranking status, private status, and whether they have established a Ph.D. program.

Consideration set dataset: A dataset of stated consideration sets for some of the candidates in the matching dataset was assembled. 1,127 surveys were sent to marketing professors who graduated during the period 1997-2009. The survey asked respondents to list (1) AMA interviews obtained, (2) campus visits received, (3) job offers received and (4) a short list of preferences among the job offers received. 313 responses were obtained. After removing incomplete responses, 153 consideration sets were kept for analysis. These consideration sets are reasonably representative, as we obtained responses from public and private universities of different ranking status.

4.1. Descriptive statistics

To conduct our analysis, a set of focal marketing departments must be determined. One possibility is to cluster departments along a number of publicly available rankings. Rather, we "let the data speak" by using the 153 usable job offer responses in our survey data to create a large relational grid of job offers between placing and hiring departments. A social network principal component analysis algorithm revealed five groups [4] of focal agents as a function of the density of transactions among them. These groups are shown in Fig. 4.

Insert Figure 4 about here

The curved arrows in Fig. 4 represent flows of offers within each group; the straight arrows represent offers between groups. The size of each arrow is proportional to the volume of offers of all arrows, such that large arrow endpoints indicate higher offer volume. The

[4] Other techniques and variables were used to form these groups with slightly different results, but the qualitative interpretation (offer asymmetry) remains the same.

asymmetry of most of these arrows invites estimation of two sets of preferences for each department, one for placing and one for hiring, to best represent the preference structure that underlies the formation of these groups. When examining the covariates that describe each group one finds further heterogeneity. This is summarized in Table 1. Group 6 includes every benchmark agent in the market.

Insert Table 1 about here

Table 1 shows that the largest concentration of top tier marketing publications is observed for Groups 1 and 2, who also are featured in ranking lists the most often, followed by Groups 3, 4, 5 and 6, in that order. On the hiring department side, most of the job positions of Groups 1 and 2 are from private universities with Ph.D. programs in marketing; Group 3 primarily offers positions in private universities with no Ph.D.; Group 4 is mixed, and Groups 5 and 6 offer mostly public positions. The ranking pattern for hiring departments is similar to that of placing departments. As it is known that top marketing publications and ranking status are attractive characteristics of candidates and departments (Close, Moulard and Monroe 2011; Zamudio, Wang and Haruvy 2013), one would in consequence expect the preference estimates of our department groups to be in descending order from Group 1 to 6, regardless of the side of the market they participate in.

4.2. Model Estimation: Individual Preference Estimates

Before applying our preference model to the data described above, two comments are in order. First, not enough degrees of freedom are available to produce a separate preference estimate for each individual candidate. Instead, we assume that every candidate placed by the same department will share that department's placing preference estimate. This amounts to examining preference at the departmental level, and thus instead of treating (say) three job candidates who graduated from Stanford as "candidates 1, 2 and 3 from Stanford," we instead treat them as "three instances of Stanford, a degree-granting university." Second, recall that the model requires that each choosing agent assess their potential partners' history of past matches, $H_{D_{c_i}tv}$. Throughout we assume $v = \infty$, meaning that agents can look as far into the past as they wish. This is reasonable in this market given *Who Went Where* archival evidence. We use the years 1997-1999 to initialize $H_{D_{c_i}tv}$, and years 2000-2009 for estimation. A small subset of focal agents had no matches during 1997-1999. To include these agents in the estimation, we collected an additional subset of 103 matches prior to 1997 for initialization.

We estimate preferences at the individual department level and then aggregate the preference metrics at the group level (following Fig. 4) and form confidence intervals. [5] Group 6 (all other departments) was selected as benchmark. Table 2 shows the results. Model I estimates group level preferences by restricting the coefficients to be equal on each side of the market, which implies that the preference structure of the market is symmetric, i.e., that every department is equally preferred on the hiring and placing sides of the market. The estimates of Model I should be interpreted as showing how appealing each department group is as compared to the benchmark group – a larger, statistically significant estimate for a department means that it is more preferred in the market, and the converse. Because preferences are restricted to be equal on both sides of the market, only one benchmark is required. The estimates from Model I show an ordering consistent with our expectation.

[5] Note that the correlations between each set of preference estimates and market participation on either side of the market are not statistically significant (for the hiring side: ρ =-.187, p=.847; for the placing side: ρ =.022, p=.892).

Model II relaxes the symmetry assumption. Now departments are allowed to be differently preferred depending on whether they are placing or hiring job candidates. The estimates shown in Model II thus should be interpreted one side at a time. Each estimate records how appealing each group is as compared to the benchmark group for that particular side of the market. A larger, statistically significant estimate for a department then means that such department is more preferred than the benchmark group of that side of the market, and the converse. Judging by the likelihood of Model I and Model II, our results indicate that estimating separate, individual preferences in matching markets conduces to better model fit. Most importantly, the preference estimates appear to be somewhat asymmetric for Groups 3 and 4. This suggests that the implicit assumption of asymmetry need not always hold. Finally, Model III also adds the consideration sets recorded in our survey as additional data to complement screening rules. These consideration sets are added for candidates only. Although consideration sets for the hiring side can potentially be imputed by "backing them out" using candidates' consideration sets, our survey data is rather sparse. Hence, we believe we do not have enough observations to credibly impute these sets. The addition of consideration set data in Model III substantially improves model fit. Furthermore, this also reveals that Groups 1 and 2 are much less asymmetric than a model without data would indicate. However, this does not apply to Groups 3 to 5. These results capture well the asymmetries illustrated in Fig. 4 and suggest that marketing departments that are equally appealing in their hiring and placing dimensions are more the exception than the norm.

4.3. Model Estimation: Preference Determinants

With our preference estimates in hand, we can proceed to examine their determinants. For example, are student publications, training, and other characteristics conducive to a high placing preference? Are public rankings such as the Financial Times MBA rankings conducive to a high hiring preference? We investigate the determinants of placing and hiring preference using a Tobit regression that relates our preference estimates to candidate and hiring department characteristics. We use observations from the year 2000 onwards. The determinants of preference are shown in Tables 3 and 4.

Insert Tables 3 and 4 about here

Interestingly, only some journals contribute to placing preference, namely the *Journal of Consumer Research* and the *Journal of Marketing Research.* Furthermore, a student's training in a specific field of research is also strongly related to placing preference. In this case, Modeling candidates appear to contribute more to this end (1.85) than CB candidates (.64), when compared to Strategy candidates, the benchmark category. Finally, rankings –specifically those featured in *Financial Times*- also contribute to placing preference. However, note that this contribution is quite small (-.002, which implies a maximum gain of .02).

Regarding the determinants of hiring preference, the *Financial Times* rankings again provide a statistically significant contribution, but their substantial value remains quite small (-.032, which implies a maximum gain of .032). Having a Ph.D. program contributes far more to hiring preference – the value associated with establishing such a program (2.01) is about the same as jumping 63 spots in the *Financial Times* ranking. If, furthermore, the hiring department is private, there is an additional gain of .72, equivalent to a further jump of 20 more spots in the *Financial Times* ranking list.

4.4. Assessing the Effect of Preference Estimates on Market Outcomes

The principal market outcomes in the marketing job market are the number of interviews, campus visits and job offers candidates can receive, as these ultimately increase candidates' chance of landing a job. If our placing estimates truly capture market preferences, then one would expect that placing preferences would be significantly related to interviews, visits, and offers. We test this specific conjecture controlling for centrality metrics as well.

Our objective is to compare the effects of preference and centrality metrics on market outcomes. To this end, we first calculated the eigenvector centrality of every department in our matching dataset. We then appended these centralities, along with the individual preference estimates used in Model II from Table 2, to our survey data. We use these estimates because they contain no consideration set data. Hence, a legitimate comparison with centralities, which are calculated using no additional information, can be made. Finally, because interviews, visits and offers may be valued differently depending on whether they are offered by either benchmark or focal hiring departments, we divide them in that manner. Merging these data resulted in a final dataset of 149 candidates, along with the number of interviews, visits, and offers they received from either benchmark or focal departments, and the eigenvector centrality and placing preference estimates[6] of each candidate's placing department.

[6] Recall that we only produced preference estimates for our list of focal departments. Therefore, placing preference estimates are not available for agents who graduated from a benchmark department. To impute these preferences, we examined the distribution of placing preferences obtained in Model 3.2. Among these, the smallest value is -.19. We impute the placing preferences of benchmark agents with the value of -.2. Imputing these values with zeros yields qualitatively identical results.

Insert Table 5 about here

Three sub-tables are shown in Table 5. Each one relates a specific market outcome (the number of interviews, visits, and offers received by a candidate from either benchmark or focal departments) to the placing preference estimate and eigenvector centrality of candidates' placing departments. For each outcome, we assess the effect of these metrics separately and simultaneously. The results show that both the effects of preference estimates and centralities are highly significant in all cases. Regressing each type of interview on the preference metrics developed in this paper generally exhibits a better likelihood than regressing them on eigenvector centrality. Interestingly, when both effects are estimated simultaneously, both are quite strong, despite the fact that both are correlated (ρ=.538, p<.05). This result is powerful, because it implies that our preference estimates are important determinants of market outcomes alongside centrality metrics. Since centrality is mostly understood as agent influence, and our placing preference estimates relate to agent preferences, these metrics may be complementary and thus quite valuable when used in tandem when investigating choices in matching markets.

5. CONCLUSION

Data from the marketing job market has allowed us to showcase our two-sided matching preference model and to verify that its resulting estimates can deepen our understanding of matching markets. Our results indicate that there are substantial asymmetries in markets in which agents participate in both sides of the market: for example, a firm may be very appealing as a supplier, but not so as a buyer, or the converse. This means that simpler metrics such as publicly available rankings may not adequately explain how transactions occur in matching markets. The better approach, we argue, is to estimate the preference structure in the market that best corresponds to the observed matches and then relate these preferences to the many metrics that characterize the agents. Our intuition is that, for most markets, asymmetry will be the norm rather than the exception. The consequences of these asymmetries have not been explored in this article, but invite further investigation.

The role of centralities also merits close examination. A plethora of articles that investigate social networks and tie them to market phenomena use centralities to characterize influence. Yet our results reveal that both centralities and preference estimates are relevant in understanding market outcomes. Because many two-sided matching markets are structurally similar (Roth and Sotomayor 1990), we believe our results from the marketing job market need not be confined to this specific matching market and can resonate across others as well. We believe that our results may be generalized to other matching markets in the sense that both metrics should matter, as one is related to influence and the other to preferences. Consequently, we suggest that, when investigating market outcomes in the context of social networks, preference estimates be produced and their effect on market outcomes in tandem with centralities be empirically assessed.

Apart from the above, we believe our results are also quite informative for both candidates and hiring schools on the marketing job market. First, the asymmetry finding is important. The notion that hiring top faculty translates to placing students well is shown to be flawed. Our findings show that graduating from a school that is able to attract top faculty talent translates into good placement *only if* these top faculties actively work with students, resulting in top publications for the students.

For marketing departments seeking to hire, we found that ranking in *Financial Times* matters somewhat in attracting good candidates. However, it is not nearly as important an attractor as having a Ph.D. program. The relative magnitude of the coefficients on ranking versus Ph.D. program strongly suggest that given limited resources, a department should invest in its Ph.D. program rather than its magazine ranking. There are clearly other important attractors not accounted for in the present work, but we expect the Ph.D. program to be a good proxy for many of them as well. Specifically, we think the main insight from this relationship is that the best way to attract good faculty is to invest in good doctoral students.

For students seeking to be hired, our results seem to capture the differential value that some fields of research and journals produce, which is in line with other studies. We find that modeling candidates fare better. This is likely because modeling departments are typically located in the top schools, so both hiring and placement for modelers happen in these schools. Thus, the finding may or may not be generalizable. Nevertheless, the results suggest that there is value for students in enhancing their quantitative skill set to ensure better placement. Likewise, the advantage of CB over strategy specialization should be interpreted in a similar fashion. In terms of publications, we find that hiring attractiveness is most apparent in the top journals. The value in those publications far exceeds the importance of the school from which the student graduates. Thus, in choosing which school to attend for their graduate studies, students should pay far greater attention to whether faculty members work with students towards publication than to the overall ranking of the school.

Our results should be understood with respect to the limitations of our work. Our model represents a step towards investigating preferences in matching markets. However current studies such as ours or Christakis et al. (2010) could make better use of matching market data to introduce parameter heterogeneity. Also, more focal agents can be studied (at the cost of computational time) to provide a more comprehensive view of the market under examination. Finally, a simultaneous approach regarding Steps 2 and 3 of our model might be desirable.

There is no debate in that we choose what we prefer, subject to constraints. This article extends this well-established idea to a newer setting: two-sided matching markets. This extension is possible, in no small part, by applying the notion of consideration sets, well-established in marketing theory, into a different domain. We believe this effort demonstrates that other fields also have something to gain from the insights that marketing theory provides. Ultimately, we hope to spur further discussion into the role that preferences play in matching markets, how to go about modeling them, and how preferences may be relevant to marketers that participate in matching markets. We expect this discussion to flourish as both technology and our own grasp of matching markets continues to develop.

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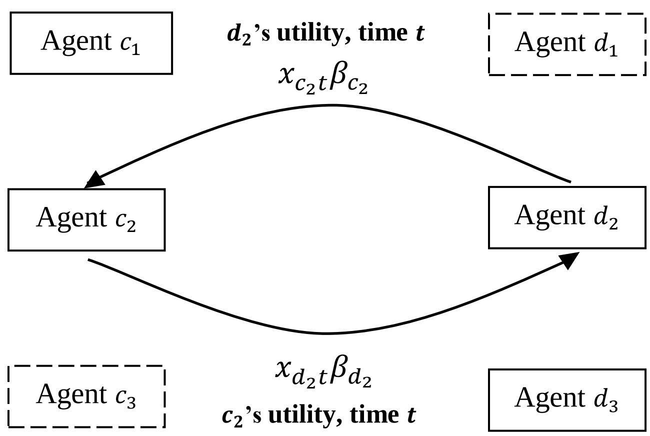
FIGURE 1
How Preferences Influence Utility in Matching Markets



The above figure represents a matching market at time t. The dashed line indicates that these market participants are not present at time t. Therefore, for participants c_3, $\delta_{c_3 t} = 0$, and for participant d_1, $\delta_{d_1 t} = 0$.

FIGURE 2
Preference Model Overview

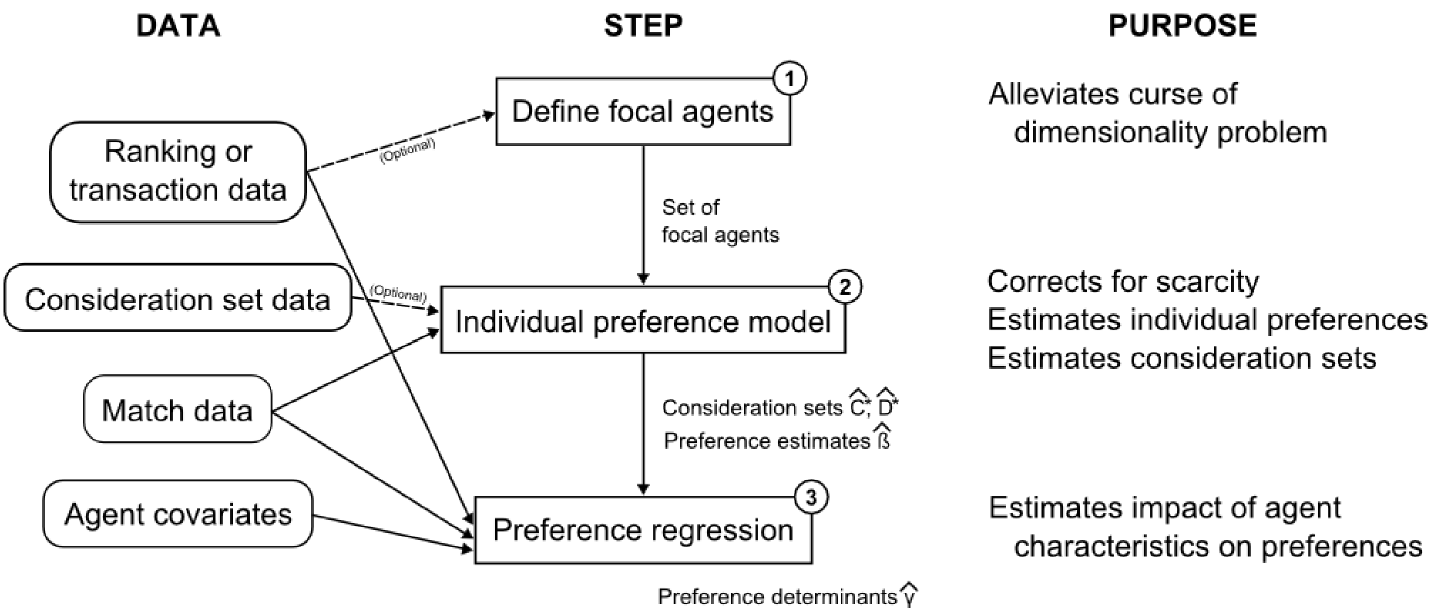


FIGURE 3
Possible Empirical Matching Distributions

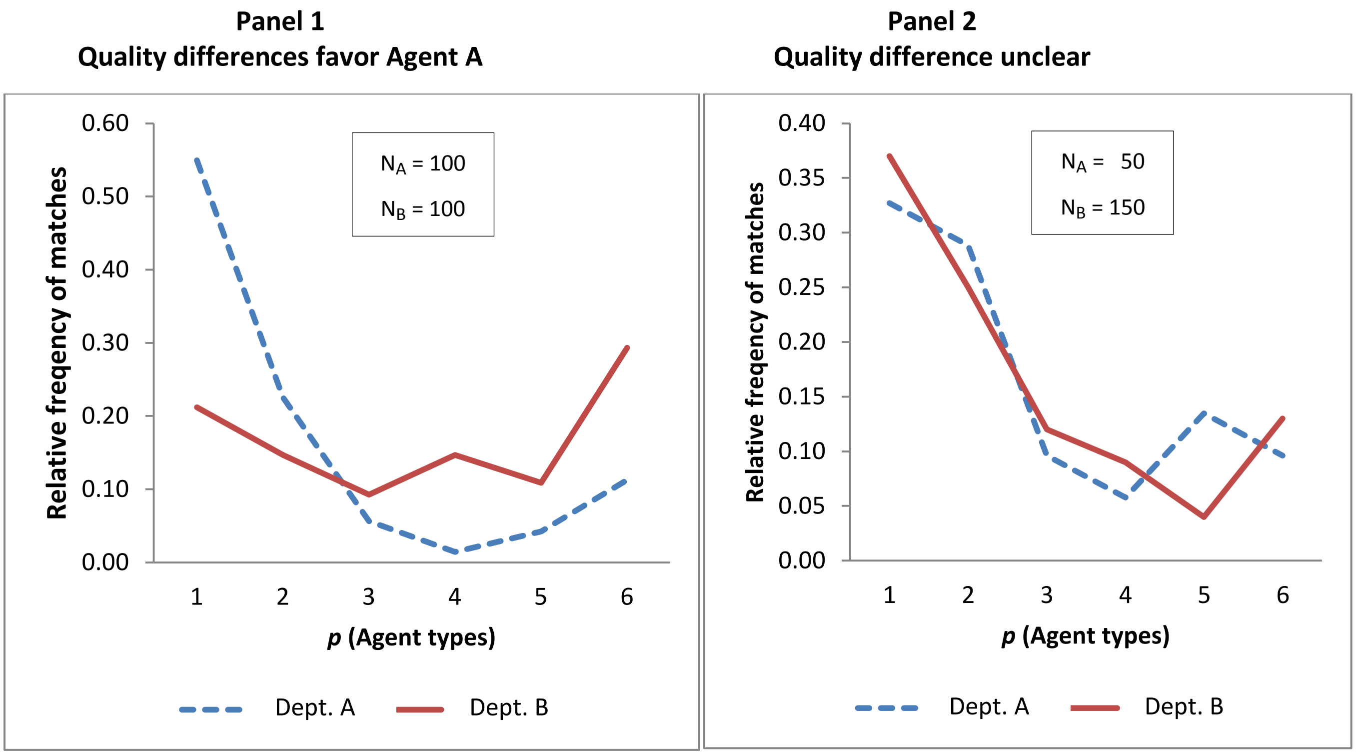
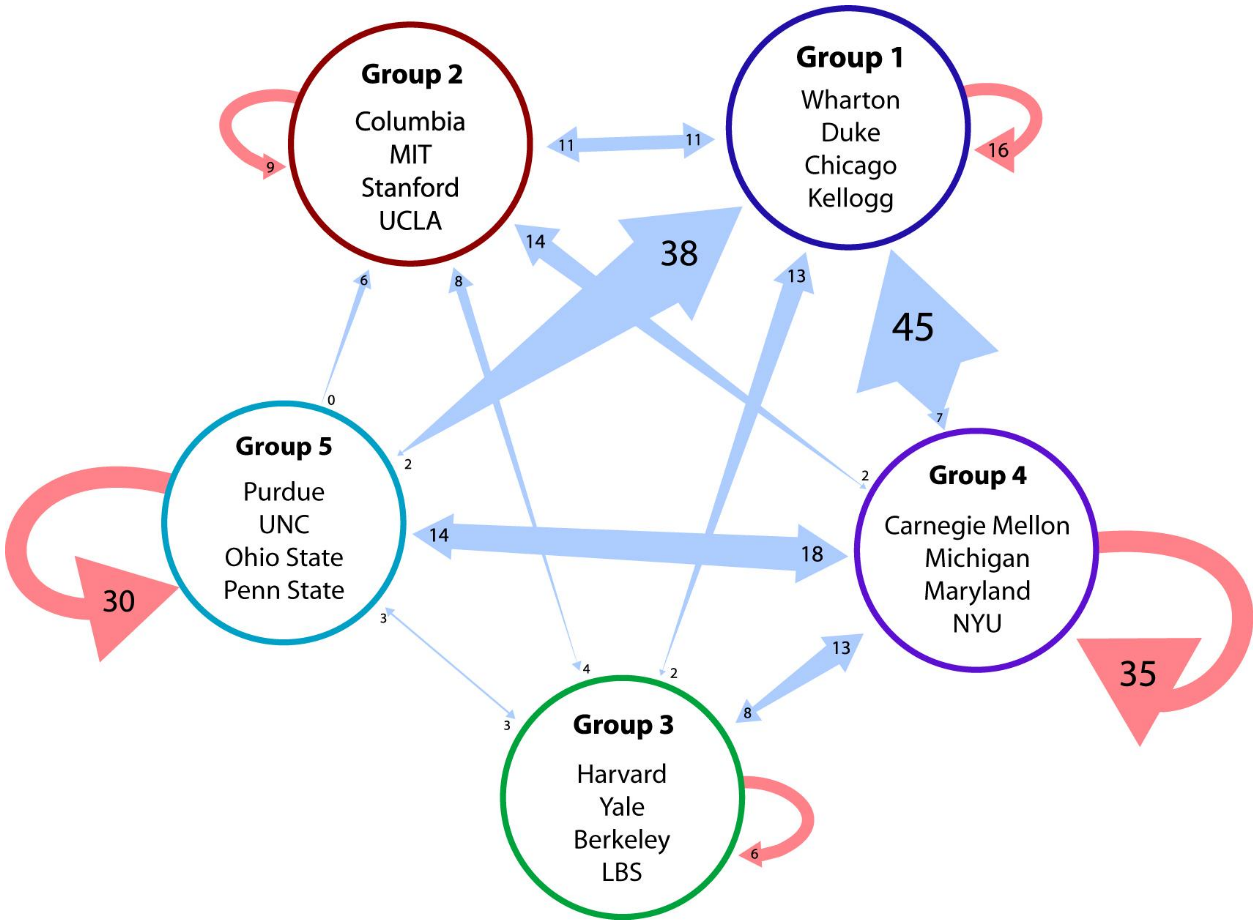


FIGURE 4
Asymmetric offer patterns in the marketing job market, 1997-2009



N=1,149. Figure was constructed using a sociomatrix of job offers. Analysis was conducted using principal components analysis. Five largest groups and representative departments shown.

TABLE 1
Descriptive statistics by department group

	Placing department descriptive statistics						
	Group 1	*Group 2*	*Group 3*	*Group 4*	*Group 5*	*Group 6*	*Total*
# candidates	57	145	48	148	197	554	1149
% private school	73.68	82.76	25	54.05	2.54	4.51	-
% schools in *Financial Times* rankings	66.67	60.69	79.17	73.65	59.90	15.70	-
# publications	97	211	65	200	290	972	1835
# publications per faculty member	1.70	1.46	1.35	1.35	1.47	1.75	-
% pubs in Top Tier Marketing journals	44.33	51.18	38.46	39.50	28.97	14.92	-
% pubs in Other Marketing journals	27.84	24.64	46.15	41.00	46.90	57.92	-
% pubs in Non-Marketing journals	27.84	23.70	15.38	19.00	23.79	27.16	-
	Hiring department descriptive statistics						
	Group 1	*Group 2*	*Group 3*	*Group 4*	*Group 5*	*Group 6*	*Total*
# total available positions	**19**	**30**	**40**	**93**	**94**	**873**	**1149**
% in private departments	78.95	90.00	45	53.76	22.34	30.58	
% in departments with Ph.D. program	100	100	82.50	100	81.91	37	
% in departments with both	78.95	90	27.50	53.76	4.26	5.50	
% featured in *Financial Times*	63.16	53.33	75	58.06	56.38	7.56	

TABLE 2
Average Group-Level Preference Estimates, 1997-2009

Marketing department	**Model I** **Symmetric preferences** Placing and hiring preferences equal	**Model II** **Asymmetric preferences + No consideration set data** Placing pref. estimate	Hiring pref. estimate	**Model III** **Asymmetric preferences + Partial consideration set data** Placing pref. estimate	Hiring pref. estimate
Group 1	1.49* (1.22, 1.76)	0.85* (0.45, 1.24)	1.20* (0.44, 1.95)	1.44* (1.10, 1.78)	1.64* (0.93, 2.36)
Group 2	1.92* (1.55, 2.28)	1.51* (1.03, 1.98)	1.33* (0.08, 2.58)	2.00* (1.51, 2.49)	1.93* (0.92, 2.93)
Group 3	1.20* (0.73, 1.67)	0.77* (0.09, 1.45)	1.98* (1.04, 2.92)	1.22* (0.68, 1.76)	2.80* (2.05, 3.55)
Group 4	0.91* (0.69, 1.12)	0.69* (0.40, 0.97)	1.07* (0.67, 1.47)	0.93* (0.66, 1.20)	1.53* (1.12, 1.93)
Group 5	0.57* (0.42, 1.16)	0.28 (-0.06, 0.62)	0.79* (0.34, 1.24)	0.25 (-0.10, 0.61)	1.19* (0.75, 1.64)
Group 6	0 (benchmark)	0 (benchmark)	0 (benchmark)	0 (benchmark)	0 (benchmark)
Likelihood	-2104.74	-1942.75		-1908.5	
Consideration sets used	0	0		153 (13.32% of N)	

N=1,149. The above results were obtained by obtaining preference estimates for all departments in Figure 4. These estimates were then averaged to form the above results. Significant estimates (95%) highlighted with *. Confidence interval shown below estimates.

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TABLE 3
Determinants of Degree-Granting Preferences

Candidate characteristics		Estimate (Standard error)
	Intercept	-.94** (.13)
Research portfolio	Mean author position	.03 (.08)
	Mean num. of authors	-.05 (.06)
	Publications in JCR	.49** (.10)
	Publications in JM	-.24 (.25)
	Publications in JMR	.42** (.15)
	Publications in MANSC	.19 (.19)
	Publications in MKSC	.23 (.17)
Field of research	CB candidate	.64** (.13)
	Modeling candidate	1.85** (.14)
	Strategy candidate	0 (benchmark)
Ranking status	Financial Times ranking	-.002** (.002)
Log(Tobit σ)		.18** (.14)
Likelihood		-1073.534

Significant estimates marked with ** (95%) or * (90%). **N=1,149.**

TABLE 4
Determinants of Hiring Preferences

Department characteristics	Estimate (Standard error)
Intercept	-.31 (0.36)
Financial Times ranking	-.032** (0.003)
Private university	.72** (0.19)
Department offers Ph.D.	2.01** (.25)
Log(Tobit σ)	.433** (0.06)
Likelihood	-743.18

Significance level 95% highlighted with **, 90% highlighted with *. N=1,149 matches. The Financial Times ranking variables were constructed as follows: for each hiring department in each match and year we recorded the ranking obtained in Financial Times. If no ranking was obtained that year, we assigned the hiring department the maximum observed value across time plus 1. So, for example, if a department was not featured in the Financial Times rankings, we assign it the value of 101.

TABLE 5
Market Outcomes as Explained by Centralities and Preference Estimates
(Estimates and Standard Errors)

Number of interviews received from…

Metric	*Benchmark departments*			*Focal departments*		
Placing preference	-2.56** (.56)		-2.21** (.66)	6.23** (.79)		4.13** (.86)
Centrality		-17.08** (5.36)	-6.13** (6.13)		58.79** (7.94)	36.77** (8.27)
Log likelihood	-455.37	-450.19	-444.87	-356.19	-357.18	-346.42

Number of campus visits received from…

Metric	*Benchmark departments*			*Focal departments*		
Placing preference	-1.28** (.28)		-1.17** (.334)	3.69** (.48)		2.72** (.52)
Centrality		-7.69** (2.62)	-1.81 (3.02)		32.78** (5.21)	17.94** (5.12)
Log likelihood	-329.47	-335.35	-329.29	-249.65	-256.01	-243.35

Number of job offers received from…

Metric	*Benchmark departments*			*Focal departments*		
Placing preference	-.80** (.18)		-.58** (.20)	1.89** (.31)		1.39** (.32)
Centrality		-6.53** (1.59)	-3.64** (1.84)		17.32** (3.29)	9.75** (3.18)
Log likelihood	-255.10	-257.23	-253.18	-161.68	-166.43	-156.70

Significant estimates marked with ** (95%) or * (90%). N=149.
Constant omitted from results table. All Tobit sigmas significant (.05).