Recruiting Rookie Faculty: School, Candidate, Competition
Anne T. Coughlan and Vithala R. Rao

Abstract

In this paper, we consider purchase behavior in the market for rookie faculty. Purchase behavior differs in this market from that in standard product markets because faculty candidates (whose research and teaching services are the "product" being "purchased") are highly differentiated, and are "produced" in a quantity of one. We account for these market characteristics in an analytic model of faculty recruiting used to predict the decision to make a job offer and the pay level that will be offered. We then test the model's predictions using primary data collected from the Marketing field. The results suggest that schools pay less attention to competitive issues in hiring than to school-specific or candidate-specific utility factors. Further, assessed candidate research potential is the consistently strongest predictor of both the decision to make an offer and the pay level offered to job candidates.

Conversation reportedly overheard between a university president and a newly-recruited famous economist at a cocktail reception honoring the faculty member:

President: I am so happy to see you!
Faculty: If you're not indifferent to seeing me, then you are paying me too little.

Introduction

Every year around the world, universities interview promising young candidates for positions on their faculties. After an often arduous interview process, culminating in an on-campus visit, the school must make a decision about to whom to give an offer, and what offer should be given. On the face of it, this appears to be a variant on the standard brand-choice problem: the buyer (here, the school) makes a decision to purchase a brand (make an offer to a junior faculty member) after inspecting the variety of brands available in the market (the array of junior faculty candidates seeking professorial employment that year). Much has already been written about brand choice that would presumably be helpful in predicting what "brand" is "purchased" (that is, what candidate gets a job offer and is hired) in this market (McFadden 1986; Guadagni and Little 1983; Bayus and Rao 1989; Blattberg and Neslin 1990, ch. 8; Bayus 1991; Corfman 1991). However, we would suggest that the faculty recruitment market has significantly different characteristics from the market for products like cereal, crackers, or even financial services. First, this is a market where buyers compete to participate in a high-involvement purchase event, rather than sellers competing to attract buyers. What is purchased, moreover, is a unique or highly differentiated "product," so that if there is competition for the candidate, purchase is not assured, given a price offered to the seller. This is because it is impossible to know all relevant facts about a candidate's set of competitive offers. In addition, the seller also has preferences over who will buy its product in this market. That is, the candidate's utility function depends not only on the salary given, but also on other factors (such as geographical location of the school, whether the school is public or private, the identity of the other faculty at the school, and so on).

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Our objective in this paper is to examine schools' "purchase" behavior in this type of market, both in terms of which candidates are most likely to get job offers, and what factors influence the size
of the pay package given. We model the school's initial offer decisions, which are based on the faculty's evaluation of candidates' qualities as revealed in the recruiting process (thus, we do not consider the "secondary" market for faculty, which occurs discretely after the close of the primary market). The paper's main contribution is therefore to model a novel choice situation which has not been examined before in the brand choice literature, and to test the model on a unique primary dataset. The findings suggest that candidates' attributes (particularly research potential) play the strongest role in both offer behavior and pay-setting, and that the external factor of competitive pressure does not influence schools' behavior.

Against this background, the rest of the paper is organized as follows. The next section describes our characterization of the recruiting process for an entry-level assistant professor in a business school and lays out a mathematical model which includes the utility functions of both sellers and buyers as well as expected competition. The third section derives an optimal pay-setting rule and describes optimal offer behavior, as well as analyzing the comparative static effects of various model parameters on the prices (pay levels) offered by buyers. The fourth section presents the results of an empirical study we conducted with regard to the 1995 recruiting of entry level Marketing faculty at several business schools. The last section summarizes our analytical and empirical results and offers some directions for further research.

A Model of New Faculty Recruitment

Our goal is to model school i's decision of to whom to give a job offer, and what pay level to offer, based on its perceptions of (a) the qualities of each candidate, (b) the expected competition from other schools that might also make an offer to each candidate, and (c) each candidate's own utility function. We therefore treat the Marketing department as the unit of analysis (see Rao and Steckel 1991, Corfman and Lehmann 1987, and Corfman and Gupta 1993 for insights into group decision-making processes). Figure 1 depicts the

![Diagram](attachment:figure1.png)

FIGURE 1: MODEL STRUCTURE FOR SCHOOL I CONSIDERING CANDIDATE J

- On-campus interviews
  - Candidate assessment by school
  - School assessment by candidate
  - Info. sharing
  - Final evaluation by school i of:
    * teaching potential
    * research potential
    * fit
    * competition for each candidate j
  - EU-maximizing salary is chosen for ea. candidate
  - EU* is compared across candidates
  - Offer(s) is/are made to top candidate(s)
process starting at the on-campus interview point and culminating in job offers to top candidates. We concentrate our modeling efforts starting at the point where final evaluation of candidate quality is undertaken. At this point, the Marketing department (or group) at school i uses the information available to finalize its perception of the expected utility generated by each candidate. The candidate(s) generating the highest expected utility receive(s) an offer, with the monetary value of the pay offered maximizing the school’s utility.3

Because our model structure is at the level of the individual school evaluating an individual candidate, we speak below of school i and candidate j. School i is posited to apply the model separately to each of the candidates under consideration; to compare the resulting expected utilities offered by all the candidates; and to maximize its utility by making (an) offer(s) to the candidate(s) it perceives to be highest-ranking.4

Our model formulation is thus just a variant on standard expected-utility models commonly used in economics (see, for example, Henderson and Quandt 1980, chapter 3). Here, the expected-utility maximizer is the school itself, and it seeks to set the total pay level to maximize its utility, given its perceptions about candidates and the market. The salary-setting problem is non-trivial, because the school must balance off the higher likelihood of hiring that a higher pay level brings (both because the candidate directly values higher pay more highly, and indirectly because paying more makes it more likely that school i “beats the competition” to hire candidate j), against the negative utility of offering higher pay levels (essentially, “paying a higher price”).

The expected utility to school i from making an offer to candidate j can be represented by the following general function:

$$EU_i^j = \text{Prob}[i \text{ hires } j] \cdot W_i^j \quad \text{where (1)}$$

$$\text{Prob}[i \text{ hires } j] = \text{school i's perception of the probability that it succeeds in hiring candidate j}$$

$$W_i^j = \text{school i's perception of the utility from hiring candidate j.}$$

We assume that:

$$W_i^j = f_w(q_i^j, t_i^j, S_i^j), \quad \text{where (2)}$$

$$q_i^j = \text{school i's perception of candidate j's research potential}$$

$$t_i^j = \text{school i's perception of candidate j's teaching potential}$$

$$S_i^j = \text{total pay offered to candidate j by school i (salary plus summer support, if any)}$$

$$\text{Prob}[i \text{ hires } j] = f_p(V_i^j, n_i^j) \quad \text{(3)}$$

$$V_i^j = f_v(S_i^j, m_i^j), \quad \text{where (4)}$$

$$V_i^j = \text{school i's perception of candidate j's utility from joining school i}$$

$$n_i^j = \text{school i's perception of the number of competing offers candidate j will get}$$

$$m_i^j = \text{school i's perception of the fit between candidate j's ideal school type and i's actual type.}$$

Following standard utility-maximization calculus techniques (see Technical Appendix A for details), we can derive the signs of comparative-static effects of $m_i^j, q_i^j, t_i^j, \text{ and } n_i^j \text{ on the optimal total pay offer, } S_i^j$. We can also consider the effect of these parameters on the likelihood of giving candidate j an offer by considering changes in reduced-form expected utility (that is, expected utility with the optimal total pay level formula substituted in) with respect to those parameters. Since school i is assumed to maximize expected utility, it follows that factors leading to higher reduced-form expected utility also increase the probability of a job offer for
These calculations generate the following comparative-static predictions about optimal salary and offer behavior:

**TABLE 1: COMPARATIVE-STATIC EFFECTS ON OPTIMAL SALARY AND OFFER BEHAVIOR**

<table>
<thead>
<tr>
<th>PARAMETER &quot;Z&quot;</th>
<th>SIGN OF (c_iS_i' / \partial Z)</th>
<th>SIGN OF (c_iU_i' / \partial Z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(m_i) (fit of school type with candidate ideal type)</td>
<td>negative</td>
<td>positive</td>
</tr>
<tr>
<td>(q_i) (research potential)</td>
<td>positive</td>
<td>positive</td>
</tr>
<tr>
<td>(t_i) (teaching potential)</td>
<td>positive</td>
<td>positive</td>
</tr>
<tr>
<td>(n_i) (number of competitors)</td>
<td>positive</td>
<td>negative*</td>
</tr>
</tbody>
</table>

*For \(n_i\) taken as a continuous variable only. If \(n_i\) is construed to change in non-incremental ways, the comparative-static effect is ambiguous.

A better fit between school \(i\)'s type and candidate \(j\)'s ideal school type is associated with a lower optimal pay level offered to \(j\) because fit and pay are substitutes for each other in candidate \(j\)'s utility function. A higher research potential leads to a higher pay level offered to candidate \(j\), as does a higher teaching potential; both imply a willingness to pay more for a more attractive "product." Finally, more expected competition for candidate \(j\) (higher \(n_i\)) leads to a higher optimal pay level offered, because success in hiring requires that school \(i\) offer more utility to candidate \(j\) than \(j\) can get from any other offer. The more competitors there are, the greater is the likelihood that one of those offers will be high; thus school \(i\)'s offer must rise concomitantly.

The model also predicts the effect of independent variables on the expected utility to school \(i\), and hence the probability of a job offer to candidate \(j\). The fit between the candidate's ideal school type and the school's actual type, \(m_i\), is positively associated with the probability that candidate \(j\) gets an offer from school \(i\), because higher fits imply a greater chance that school \(i\) can "beat the competition" to hire candidate \(j\). Increases in candidate \(j\)'s research or teaching potential likewise increase the reduced-form expected utility from giving \(j\) a job offer, and thus increase the likelihood of an offer being tendered. Finally, an increase in the number of competitors, \(n_i\), decreases the reduced-form expected utility to school \(i\) of making an offer to candidate \(j\).

We proceed to test the model's predictions, and to gain insights into the relative importance of various predictive factors in offer behavior, using an original dataset collected in the context of the rookie market for Marketing professors.

**Empirical Study**

We test the general model above in three ways in this section. First, we parametrize the general functions posited and estimate these functions using our data, using the model estimates of expected utility to predict which candidates will receive offers. We compare the results of this exercise with actual offer behavior to assess the viability of the model specification. Second, we specify a logit model of offer behavior, using as regressors the exogenous variables of the general model above, to see how well the joint set of variables predicts offer behavior as a whole. Third, we test what descriptors of candidates and schools are the strongest predictors of pay-setting behavior. Below, we first describe the data collection procedures and the dataset itself, and then discuss the three estimations in turn.

**Data Collection and Data Description**

Our data were collected in two waves in the Spring of 1996, pertaining to the rookie Marketing faculty job market that occurred in the 1995/96 school year. We first circulated a questionnaire to the participants at the Marketing Science conference held in Gainesville, Florida in March 1996 by including it in their registration packets. About 4 weeks later, we sent out a reminder postcard to all the faculty attendees at the conference. In June 1996, we sent a second wave of questionnaires to 75 faculty at a broader base of schools. This process yielded 52
responses from 41 distinct schools. The respondents were generally professors who had taught for a number of years at the school, who played a significant role (as a member or as the Chair) in the recruiting activity at the school, and who therefore have considerable experience judging candidates.

Missing data forced us to discard 18 of our 52 observations. The remaining 34 observations came from 28 distinct schools. Because our focus is at the school level, we used just one observation per school, using seniority of the respondent as a criterion for keeping an observation in the dataset. Our logic is that more senior faculty are likely to have better information about, or greater influence over, the details of the recruiting process. We were therefore left with a sample of 28 distinct Marketing departments, who conducted a total of 102 on-campus interviews. Fifty-three of the 102 campus visits, or 52 percent, resulted in job offers.

Almost all schools recruited in the two most recent recruiting years. In our final sample, 18 percent of schools were located outside the U.S., and 36 percent were private schools. We found no evidence that non-U.S. schools behaved differently than did U.S. schools in terms of their interviewing or offer behavior. There was a fairly even split between those schools looking for the “best athlete” candidate, versus those looking for a specific skill set. As well, there was a broad spread of interests in hiring in quantitative, behavioral, and managerial areas.

The schools also varied widely by rank, using the Gourman Report (1997) as a rating source. The Gourman Report is an independent report that ranks U.S. business schools on overall quality, including faculty and research quality (not just MBA placement and program rankings). Our sample is a good cross-section of schools, with 6 in Gourman’s top 20; 8 ranked from 21 to 50 in the Gourman Report; 9 ranked below 50; and 5 foreign (hence, unranked) schools.

Our questionnaire focused on recruiting activity by each school during the most recent year in which they did on-campus interviews, and elicited the following data:

(1) judgmental data enabling us to calibrate utility functions for candidates and schools; these data included questions on the judged utility to the school of a given candidate profile and questions asking the respondent’s judgments of a candidate’s utility for different offers of salary and fit with the school.

(2) actual recent experience with candidates interviewed on campus; this included for each candidate actual ratings on research potential, teaching potential, fit, whether or not an offer was made to the candidate, and the number of other schools who might make an offer to the candidate; and judgments on the percentiles of the distribution of salary offered to the candidates when making an offer in the year in which their school recruited; and

(3) the role the respondent played in the recruiting process and the school at which the respondent teaches.

In order to keep the respondent’s task meaningful and to maximize response rates, we restricted ourselves to asking the minimum number of questions necessary to calibrate the school’s perceptions of its own utility function and that of the candidate. The questionnaire included two questions to elicit a school’s utility function. One candidate’s profile was first fixed at a given teaching potential or “fit” score and research potential or “quality” score. The faculty respondent was asked to give his assessment of the quality score for a second candidate, characterized by a pre-specified fit score, that would make that second candidate as attractive to the school as the first candidate (under the assumption that both are given the same compensation and both are equally likely to join the school). A similar question was asked for a third candidate with a different fit score.
The questions used to calibrate the school's perception of the candidate's utility function were similar, except now the variables used were fit between the candidate's ideal and this school's actual type, and pay plan offered. These questions are thus in the same spirit as those used in a conjoint study (Green and Srinivasan 1978, 1990).

The data we collect are retrospective, due to the nature of this research. Confidentiality concerns prevent us from collecting recruiting data as the recruiting season actually unfolds. To minimize any negative effects of collecting retrospective data, we surveyed respondents only a few months after the actual recruiting season. As this is a high involvement activity, we believe the respondents' memories are very good.

**Predicting Offer Behavior Using a Parametrization of the Model**

Using the general model specification in equations (1) - (4), we parametrize the functions in (2), (3), and (4) using functional forms that meet the restrictions described above. We then fit the parameters for these functional forms using our original data, and use the fitted model to predict which candidates will get offers. We then compare these predictions with the true offer behavior to examine the validity of the model specification.

Equation (2), school i's perceived utility function should it be successful in hiring candidate $j$, is specified as:

$$W_{ij} = \tau_j \cdot \ln \left( q_{ij} \right) + \eta_j \cdot \ln \left( t_j \right) - k_j \cdot S_{ij}, \quad (5)$$

where $\tau$, $\eta$, and $k$ are school-specific parameters to be estimated ($k$ in particular measures the marginal disutility of paying $1$ more to candidate $j$, and thus translates dollars of pay into negative units of utility). This functional form reflects diminishing marginal utility for teaching potential and for research potential; separability between the two; and a constant disutility of granting higher pay levels, consistent with the functional form characteristics posited in the general model above.

Equation (4), school i's perception of the utility function of candidate $j$, is specified as:

$$V_{ij} = \sigma_i \cdot \ln \left( S_{ij} \right) + \theta_i \cdot \ln \left( m_{ij} \right), \quad (6)$$

where $\sigma$ and $\theta$ are school-specific parameters to be estimated: that is, we assume that school i perceives all candidates to place the same (positive and diminishing) marginal utility on incremental increases in salary or fit, although school i's perception of the fit between its school type and each candidate's ideal may of course vary.

Finally, school i's perception of the probability that it will be successful in hiring candidate $j$ (represented in general form in equation (3) above) is just the probability that school i offers candidate $j$ more utility than any other school making candidate $j$ an offer. This is given by:

$$\text{Prob}[i \text{ hires } j] = \left[ G(V_{ij}) \right]^{n_i} \quad (7)$$

where $n_i$ is the number of schools that i perceives are competing to hire candidate $j$, and $G(\cdot)$ is the cumulative density function of all $V_{ij}$'s offered to $j$ (by other schools $k$) that are lower than $V_{ij}$.

In order to more completely specify $G(\cdot)$, we posit that school i assumes that $\ln \left( S_h \right)$ and $\ln \left( m_i \right)$ are independently distributed as normal variates with means and variances of $(\mu_1, c_1^2)$ and $(\mu_2, c_2^2)$ respectively. Based on these assumptions, $V_{ij}$ is also normally distributed, with mean and variance of:

$$\mu = \sigma_i \cdot \mu_1 + \theta_i \cdot \mu_2, \quad \text{and} \quad c^2 = \sigma_i^2 \cdot c_1^2 + \theta_i^2 \cdot c_2^2 \quad (8)$$

Then, $G(V_{ij}) = \Phi(\frac{V_{ij} - \mu}{c})$ where $\Phi(\cdot)$ is the cumulative distribution for the standard normal distribution. Thus school i's perception of the probability that it will be successful in hiring candidate $j$ is:

$$\text{Prob}[i \text{ hires } j] = \Phi \left[ \frac{V_{ij} - \mu}{c} \right] s_j \quad (9)$$
Then substituting equations (5), (6), and (9) into equation (1) gives us the specific parametrized form for the model. We use our questionnaire data to fit the model parameters, thus deriving a measure of the expected utility for each candidate with a specific offer. We use this information to predict job offer behavior, where a candidate is given a rank between 1 and 56 based on our model, and a probability of hiring (Prob[hires i]), referred to below as “Probability of Hiring”).

Table 2 reports on the correspondence between our model predictions and actual offer behavior. We expect more top-ranked and fewer low-ranked candidates to receive offers. Indeed, over 80 percent of the top-ranked candidates using the EU criterion from our model actually did get offers, as did almost 54 percent of the second-ranked candidates.

Neither of the components of EU criterion (“Utility if Hired” and “Probability of Hiring”) predict hiring of the top-ranked candidate as well as the total EU criterion does (82.1 percent for EU, versus only 75 percent for “Utility if Hired” and 71.4 percent for “Probability of Hiring”). These results suggest that on balance, the schools in our sample weight the probability of hiring as less important than the perceived utility a candidate promises.

<table>
<thead>
<tr>
<th># of Candidates</th>
<th>% Receiving Offers Using:</th>
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<tbody>
<tr>
<td></td>
<td>EU Criterion:</td>
</tr>
<tr>
<td>Top-ranked</td>
<td>28</td>
</tr>
<tr>
<td>2nd-ranked</td>
<td>28</td>
</tr>
<tr>
<td>3rd, 4th, or 5th-ranked</td>
<td>46</td>
</tr>
</tbody>
</table>

Among schools making just one job offer (n=13), the EU criterion correctly classifies 69% of candidates getting an offer as top-ranked, while the “Utility if Hired” criterion correctly classifies only 54% and the “Probability of Hiring” criterion correctly classifies 69%. This suggests that if only one offer is to be made, the probability of success takes on somewhat
TABLE 3: NAIVE RANKING MODELS FOR PREDICTING OFFER BEHAVIOR

<table>
<thead>
<tr>
<th></th>
<th>Ranked by Research Potential Alone</th>
<th>Ranked by Teaching Potential Alone</th>
<th>Ranked by (Research Potential + Teaching Potential)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># of candidates of rank:*</td>
<td>% receiving offers:</td>
<td># of candidates of rank:*</td>
</tr>
<tr>
<td>Top-ranked</td>
<td>39</td>
<td>69</td>
<td>44</td>
</tr>
<tr>
<td>2nd-ranked</td>
<td>22</td>
<td>68</td>
<td>23</td>
</tr>
<tr>
<td>3rd-, 4th-, or 5th-ranked</td>
<td>41</td>
<td>27</td>
<td>35</td>
</tr>
</tbody>
</table>
|                        |                                     |                                   | 44                                                 | 25         | 70

*: Number can be greater than number of schools, for ties in ranks.

greater importance; there is a greater cost to being unsuccessful.

To investigate the incremental predictive power of the fitted model compared to some naive benchmarks, we report in Table 3 the percentage of first-, second-, and lower-ranked candidates receiving offers, where the rankings are determined (a) solely by research potential, (b) solely by teaching potential, and (c) by the sum of research and teaching potential scores.

None of the ranking models appears to predict offer behavior better than our EU model criterion. In particular, ranking candidates by teaching potential alone appears a considerably poorer option, with only 55 percent of top-ranked candidates receiving offers, while 61 percent of second-ranked candidates do. The combined (teaching + research potential) ranking system also shows a higher percentage of second-ranked candidates getting offers than first-ranked ones, and only 70 percent of top-ranked candidates getting offers, versus over 82 percent of candidates ranked top by the EU criterion getting offers. Our EU model thus appears to predict offer behavior better than more naive benchmark ranking models do.

Predicting Offer Behavior: Logistic Regression

We also used logistic regression to predict offer behavior based on the model’s comparative-static predictions in Table 1 (thus, n=102). We pooled data across schools, using each campus visit as an observation. We estimated logistic regressions of offer behavior of the following form:

$$\ln\left(\frac{\text{Prob(Offer)}}{1 - \text{Prob(Offer)}}\right) = \beta_0 + \beta_1 \cdot \text{RESPOT} + \beta_2 \cdot \text{TCHPOT} + \beta_3 \cdot \text{FIT} + \beta_4 \cdot \text{COMPETNUM},$$  \hspace{1cm} (10)

where:

- RESPOT = i’s perception of j’s research potential
- TCHPOT = i’s perception of j’s teaching potential
- FIT = i’s perception of the fit between j’s ideal school type and i’s actual type
- COMPETNUM = i’s perception of the number of competing schools making an offer to j.
Expected coefficient signs, corresponding to the comparative static effects in Table 1, are included in parentheses below each independent variable.

On our 11-point scales, research potential (RESPOT), teaching potential (TCHPOT), and fit (FIT) have means of 7.16, 7.57, and 7.17 respectively. These relatively high values should not be a surprise, given the pre-screening that occurs before the on-campus interview. The mean perceived number of competitive offers (COMPETNUM) is 3.42.

Table 4 presents logistic regression results (run using the LOGISTIC procedure in SAS) for equation (10). Model 1 in Table 4 reports logistic regression results for equation (10) itself. Although all regressors have the expected signs, only the coefficients on research potential (RESPOT) and fit (FIT) are significant. However, the model as a whole has a very high significance level, and correctly predicts two-thirds of the observations.

Because of suspected multicollinearity problems in Model 1, we further estimated the model excluding first the number of competitors (COMPETNUM) (Model 2), and then the fit between school type and candidate ideal type (FIT) (Model 3). The number of competitors is never a significant regressor. This is not surprising, given the ambiguous comparative-static results of the number of competitors on expected utility discussed above. The high correlations between COMPETNUM and RESPOT (0.483) and between COMPETNUM and TCHPOT (0.278) also suggest the possibility that school i infers a higher number of expected competitors for higher-potential candidates, so that any additional “pure” effect of competitive numbers on probability of a job offer is simply obscured in the data. The fit between candidate ideal type and school actual type remains a significant regressor in Model 2. Teaching potential (TCHPOT) is significant at about the 10 percent level in Model 3, in the absence of FIT (with which it is strongly correlated at 0.344).

These results suggest that research potential is a consistently strong predictor of offer behavior, but teaching potential and fit between the candidate’s ideal and the school’s actual profile also play a role. Cross-tabulation of the offer data by teaching potential and by research potential shows that no candidates with teaching potential ratings lower than 5 were given offers, but that for all ratings above 5, the frequency of offers was about 60 percent. Thus, while there is definitely a value

<table>
<thead>
<tr>
<th>TABLE 4: LOGISTIC REGRESSION RESULTS</th>
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<tbody>
<tr>
<td>(DEPENDENT VARIABLE = LN[PROB(OFFER)/[1-PROB(OFFER)]], N=102 OBSERVATIONS)</td>
</tr>
<tr>
<td>Parameter and Expected Sign</td>
</tr>
<tr>
<td>RESPOT (+) [j’s research potential]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>TCHPOT (+) [j’s teaching potential]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>FIT (+) [fit between i’s type and j’s ideal type]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>COMPETNUM (-) [expected number of competitors to hire j]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Model chi-square (degrees of freedom) [Signif. level for model]</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>% correctly predicted</td>
</tr>
<tr>
<td>% offers correctly predicted</td>
</tr>
<tr>
<td>% non-offers correctly predicted</td>
</tr>
</tbody>
</table>
placed on teaching, the data suggest that on the margin, better teaching potential does not produce a much higher offer likelihood. In contrast, research potential ratings of 9 or better are associated with greater than a 75 percent offer frequency, and the frequency of offers rises throughout the research potential range.

The perceived stiffness of competition for candidate j is not a strong predictor of offer behavior, but this too is consistent with the countervailing forces that increased competition implies (i.e., both a lower probability of hiring and a more attractive profile).

Using the coefficients in Model 2, we can calculate the impact on probability of an offer that would result from a one-point increase in research potential (RESPOT), teaching potential (TCHPOT), or fit (FIT). The predicted probability of an offer, setting each of these variables equal to their mean values (of 7.16, 7.57, and 7.17 respectively), is 52.5%. Holding the other variable values constant at their mean values, a one-point increase in the value of RESPOT increases the probability of an offer by 8.6 percentage points, to 61.1%. A one-point increase in TCHPOT increases the probability of an offer by 3.5 percentage points, to 56.0%; and a one-point increase in FIT increases the probability of an offer by 5.2 percentage points, to 57.7%.  

We used a jackknife procedure to validate the three models presented in Table 4. Because of the imbalanced sample (with OFFER=1 for 53 of the 102 observations), we randomly deleted four observations where OFFER=1 to obtain an equal number of offers and non-offers. Offers and non-offers were randomly paired to get 49 pairs. We then estimated the logit model 49 times, each time deleting one pair. We used the estimated models to predict the deleted pair, and created a hit-miss table for each pair. Table 5 presents a summary of the hit-miss results. These jackknife predictions are extremely good.

While the models seem to do a good job in predicting offer behavior, we can also compare their performance with some reasonable benchmark models that could alternatively be proposed. A model using only teaching potential does a considerably worse job of predicting offer behavior, with only 55 percent of observations correctly predicted. A model with research potential alone correctly predicts just 57 percent of observations. Thus, a single-factor naïve model does worse than our more complete model.

In sum, offer behavior appears to be driven primarily by factors concerning the school and the candidate specifically, and not outside effects such as competitive offer behavior. Research potential and fit between the school’s type and the candidate’s ideal type are clearly the most important drivers of offer behavior, with teaching potential being an important determinant only in the absence of the fit variable. The model is able to correctly predict two-thirds of observations, performing better than simple one-factor naïve models, and about as well as carefully chosen two-factor models.

<table>
<thead>
<tr>
<th>TABLE 5: JACKKNIFE PROCEDURE RESULTS</th>
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<tbody>
<tr>
<td><strong>Number of Actual / Predicted Observations</strong></td>
</tr>
<tr>
<td><strong>Model:</strong></td>
</tr>
<tr>
<td>Model 1</td>
</tr>
<tr>
<td>Model 2</td>
</tr>
<tr>
<td>Model 3</td>
</tr>
</tbody>
</table>
Salary Results

In our analysis of salary-setting behavior, we investigate whether the same factors influence the size of the job offer as influence the generation of the offer. In addition to our model variables, we consider three dummy variables that can help control for factors external to our model that influence rookie professor total pay. We expect a dummy variable, PRIVATE (1 if the school is private, 0 if the school is public) to have a positive coefficient in our regressions, consistent with the historical observation that private schools have offered higher pay levels than public schools. The second and third dummy variables represent ranking categories of schools in the Gourman Report data. One such variable, TOPRANK, equals 1 if the school in question is in the top 20 of the Gourman schools; the other, MIDRANK, equals 1 if the school's Gourman rank is from 21 to 50. While we have no a priori predictions about the sign of the coefficients on these ranking variables, some have believed that top-ranked schools pay less than lower-ranked schools, believing that they need not bid as aggressively for top talent as lesser-ranked schools. Competing against this conjecture is another belief that lower-ranked schools may pay less because they are money-constrained, which in turn is a causal factor in their low rankings. Regardless of which factor might be dominant, we deem it important to control for these factors by considering the variables. In fact, the top-ranked dummy’s coefficient is always insignificant in the salary regressions; we therefore suppress it for clarity and focus on the mid-ranked dummy (MIDRANK) and the dummy for private/public institutions (PRIVATE) in our discussions below.

Our sample consists of all 53 campus visits that culminated in a job offer. When multiple offers were made, confidentiality issues forced us to assume that all candidates received the same financial offer. The mean estimated total pay offer (including salary and summer support) is $86,300, and ranges from about $50,000 to over $104,000. The research, teaching, fit, and competitive variables have slightly higher means than in the offer data, but the range and standard deviations are generally smaller (all of which is consistent with the fact that these are presumably the “best” candidates). Forty-two percent of the offers were given by private schools.

Table 6 reports OLS regression results for four models predicting pay-setting behavior. In model 1, including all four regressors suggested by our analytic model, the coefficients on research and teaching potential are significant, but not those on fit or competition. The overall model fit is also significant. On our 11-point scale, a one-point increase in research potential is associated with a pay increase of $2,780, while a one-point increase in teaching potential is associated with a pay decrease of $2,760.

Models 2 through 4 add, respectively, MIDRANK, PRIVATE, and both control variables to the regression equation. Overall model fits rise with the inclusion of these control variables. Research potential remains a robustly positive influence on total pay levels, with a one-point increase in research potential translating into a pay increase of from $2,370 to $3,100. The coefficient on teaching potential remains negative, but becomes insignificant in the presence of the private school dummy variable (probably explained by the negative correlation between TCHPOT and PRIVATE). The FIT variable has the expected negative sign (candidates with better fit between their ideal and the school’s actual type tend to get paid less, because they do not need to be wooed as hard with high pay levels to come to school i), but the effect is never statistically significant. The perceived number of competitors for candidate i never has a significant influence on total pay levels, although again the coefficients in all models have the expected positive sign. Finally, both MIDRANK and PRIVATE have significant and positive coefficients; mid-ranked schools give a pay premium of from $8,480 to $9,460, while private institutions give a pay premium of over $10,000. A mid-ranked private institution (see model 4) gives a pay premium (salary plus summer support) over a non-mid-ranked public institution of almost $19,000! The significant positive coefficient on
MIDRANK is consistent with the hypothesis that mid-ranked schools see themselves as competing with top-ranked schools, and seek to compensate for the difference in overall rankings with a higher pay package.

We found the coefficients on TCHPOT and COMPETNUM to be counterintuitive and sought explanations for the results. As for COMPETNUM, the same logic could be at work here as in the offer data: COMPETNUM is significantly correlated with both RESPOT (0.42) and TCHPOT (0.36), making it difficult to infer any pure effect of competition on the setting of pay levels. An inspection of the mean level of pay offers across different levels of competition shows no pattern at all, suggesting that competition in fact may not drive pay offer levels.

One hypothesis for the significant negative (or, in models 3 and 4, insignificant) coefficient of TCHPOT is simply that in reality, better teachers do not command higher pay levels, much though schools say they value better teaching. It could be that good teaching ability is a more common asset than good research ability, and it therefore fails to command a pay premium. This is borne out in the data, where candidates getting job offers who were rated with teaching potential of 5 or 6 received an average total pay level of close to $100,000; those rated with teaching potential of 7 or 8 received average total pay of about $82,000; and those rated with teaching potential of 9 to 11 received an average total pay level of about $85,000.

The range of TCHPOT among candidates who received offers is only from 5 to 11 on an 11-point scale, suggesting that poor teachers are never given job offers at all. The implication is that there really is a premium to good teaching: it is the difference between getting and not getting a job offer at all! This conclusion is consistent with the findings in the offer regressions, where the frequency of offers does not vary a great deal over teaching potential ratings greater than 5; but no candidates with teaching potential ratings lower than 5 received offers.

### TABLE 6: PAY-SETTING BEHAVIOR: OLS RESULTS
(DEPENDENT VARIABLE = PAY; N=53 OBSERVATIONS)

<table>
<thead>
<tr>
<th>Parameter and Expected Sign</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>RESPOT (Δ) * * * (j's research potential)</td>
<td>2.78 (0.04)</td>
<td>2.37 (0.07)</td>
<td>3.10 (0.01)</td>
<td>2.71 (0.03)</td>
</tr>
<tr>
<td>TCHPOT (Δ) * * * (j's teaching potential)</td>
<td>-2.76 (0.08)</td>
<td>-2.80 (0.06)</td>
<td>-1.73 (0.23)</td>
<td>-1.82 (0.19)</td>
</tr>
<tr>
<td>FIT (Δ) * * * (fit between i's type and j's ideal type)</td>
<td>-1.18 (0.33)</td>
<td>-1.34 (0.25)</td>
<td>-1.39 (0.20)</td>
<td>-1.53 (0.15)</td>
</tr>
<tr>
<td>COMPETNUM (Δ) * * * * (expected number of competitors to hire j)</td>
<td>0.61 (0.48)</td>
<td>0.90 (0.28)</td>
<td>0.13 (0.87)</td>
<td>0.42 (0.59)</td>
</tr>
<tr>
<td>MIDRANK (Δ) * * * * * (dummy=1 if school is ranked 21-50 in Gourman ranking)</td>
<td>*</td>
<td>9.46 (0.03)</td>
<td>*</td>
<td>8.48 (0.04)</td>
</tr>
<tr>
<td>PRIVATE (Δ) * * * * * * * (private/public school dummy)</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Adj. R-squared</td>
<td>0.13</td>
<td>0.20</td>
<td>0.27</td>
<td>0.33</td>
</tr>
<tr>
<td>F</td>
<td>2.96</td>
<td>3.55</td>
<td>4.93</td>
<td>5.21</td>
</tr>
<tr>
<td>Signif. of F</td>
<td>0.03</td>
<td>0.008</td>
<td>0.001</td>
<td>0.0004</td>
</tr>
</tbody>
</table>
The negative correlation between PRIVATE and TCHPOT could also provide a clue: if private schools routinely rate candidates’ teaching abilities lower than public schools do (or tend to ask lower-teaching-potential candidates back to campus), controlling for the private/public school dichotomy would cause the spurious negative and significant relationship between teaching potential and total pay to disappear. However, the ratings of teaching potential do not have a significantly different mean among private schools than among public schools (t=0.3681, 100 d.f., significance level=0.7136), so this is unlikely to be the reason behind the results.

To validate the salary models above, we used a jackknife procedure, holding out one of our 53 observations at a time and re-estimating each of the four OLS models on the remaining 52 observations. In each instance, we used the re-estimated model to predict the salary that would be offered by the remaining school. All four models perform relatively well: their MAPEs (mean absolute percentage errors), respectively, are 3.14%, 3.25%, 2.59%, and 2.71%. Given the mean pay level of $86,300, these errors are all less than $3,000 in magnitude.

In summary, research potential and teaching potential have the greatest impact on rookie professor pay levels. Research potential has a strongly positive and consistent effect on pay, as do the private/public dummy variable and the dummy variable for mid-ranked schools. Higher teaching potential is associated with a lower pay level, although the relationship becomes insignificant in the presence of the private/public school dummy. There is a slight, but insignificant, negative relationship between fit (of the candidate’s ideal school type with school i’s actual type) and total pay. The expected number of competitors appears not to affect pay levels at all, although any pure competitive effect may be obscured by the high correlation between expected number of competitors and both research and teaching potential.

Conclusions and Future Research Directions

Our model fits both the offer behavior and the salary-setting behavior we observe in the academic recruiting market quite well. The model’s power to predict offer behavior in particular is excellent. In general, factors that affect the school’s utility play a larger role than factors affecting the probability of hiring (although fit does significantly affect the size of the salary offered). The most persistent departure of the data from model predictions is in the competitive arena. However, several alternative explanations exist for the lack of significance of competitive factors in our model:

- Schools may simply not act “strategically” in deciding to whom to make job offers, and at what salary level, but instead only care about their own utility if they do succeed in hiring the chosen candidate(s). However, in a subset of 7 schools that failed to make an offer to the candidate with the highest “Utility If Hired,” 6 in fact gave a job offer to a candidate with a higher “Probability of Hiring.” While this is of course a very small sample, the finding suggests that when the school decides not to make an offer to a highly desirable candidate, it instead turns to a “safer” one that is more likely to join the faculty.

- Schools may deal with the problem generated by a low probability-of-hire (but highly desirable) candidate by increasing the total number of offers tendered. In our data, among the 21 schools that did give a job offer to the candidate promising the highest “Utility If Hired,” the correlation between the total number of job offers made and the probability of hiring the highest “Utility-If-Hired” candidate is -0.29565, marginally significant. Thus, this may explain part of the phenomenon.

In the last several years the market for Marketing faculty has progressed from being more of a “seller’s” market to being more of
Consideration of the gaming and interplay between a candidate and a school. While our focus in this paper is on the school's perception of the process, which is appropriate given our interest in offer and salary-setting behavior, a more “full-equilibrium” approach, involving estimating candidate utility functions directly from candidate data, could shed light on the “market clearing” phase of the job market.

- Examination of the impact of prior information-sharing has on the ex post beliefs schools have about both candidate qualities and the competitive set (in other contexts, information-sharing is investigated by Clarke 1983, Gal-Or 1985, Li 1985, and Shavell 1994).
- Collection of data during the actual process of recruiting, rather than waiting until the process is complete.
- Use of multiple informants and more full-fledged conjoint-type data collection to estimate utility function parameters, as well as data collection throughout the entire recruitment process.
- Consideration of the interactions among multiple candidates receiving an offer from the same school and their effects on the total number of offers made.
- Application of the approach to other similar markets such as that for fine art or free-agent sports stars, where the product being sold is unique, where buyers compete to buy the product, and where indeed the seller might care who the buyer is.

These directions suggest that the beginning we have made in investigating purchase behavior in the faculty recruitment market can be augmented in several interesting and insightful ways in future research. For the present, it is encouraging to note that the model posited does appear to represent actual behavior well, and that the foundation laid here can be extended in future work.
REFERENCES


ENDNOTES

1 We thank Eitan Muller for relating this story to us.

2 With all due respect to Ph.D. students seeking faculty employment, we will use standard market terminology to discuss the model here. Thus, faculty candidates may be described as “sellers” or as the “product” being purchased by a university, which may in turn be described as the “buyer.”

3 In particular, then, we do not model the general equilibrium process of market clearing in the rookie Marketing faculty labor market, but rather the initial job offer behavior of school i. While the equilibrium offer acceptance process is clearly an interesting and important research issue (see for example Kiefer and Neumann 1989, Devine and Kiefer 1991, and working papers such as Bowlus, Kiefer, and Neumann (1996) and Christensen and Kiefer (1996)), it was deemed too confidential to attack at
this point, because it would require each school responding
to our survey to reveal the identities of each candidate
interviewed.
4 Note that because one school's perception of a given
candidate may differ from another's, our model is consistent
with a particular candidate receiving offers from some,
but not all, schools that s/he visits.
5 Technical Appendix A (available from the authors)
provides a discussion of the ambiguity of the comparative-
static effect of number of competitors on offer behavior
when number of competitors is constrained to be an integer
value.
6 Some attendees who were students were clearly not
appropriate respondents to our questionnaire. We received
no responses from students, as the questionnaire was
clearly targeted toward faculty. There were 261 faculty
registered at the conference, from 113 distinct schools.
Seventy-two of the 113 schools were in the U.S. and 41
were outside the U.S. Because we do not know how many
schools did not recruit junior faculty at all, it is unclear
what the true potential universe of respondents is, but it is
somewhat less than the total number of schools represented
at the conference.
7 The schools targeted included 21 of the top 25 business
schools as ranked by Business Week magazine (Byrne and
Leonhardt 1996), as well as 34 other major public and
private business schools in the U.S. and 7 outside the U.S.
The second questionnaire differed slightly from the first,
but the changes are not likely to materially affect the results.
In the second questionnaire, we asked a more finely-
grained question about the percentile range in which the
respondent's school's salary offer fell, and asked for utility
values (in points out of 100), not just for tradeoffs,
regarding school and candidate utility functions.
8 Of the 28 schools, 23 were in the U.S. and 5 were outside
the U.S. This represents a 32 percent response rate for
U.S. schools sampled and a 12.5 percent response rate for
non-U.S. schools sampled.
9 Even using one of the more popular rankings, that
reported by U.S. News and World Report (Lord 1997),
we still get variation in school "quality." Eight of our 28
schools fell into the U.S. News and World Report's top 25
schools; 8 fell into ranks 26 through 50; 7 were ranked
below 50; and 5 were foreign (hence, unranked).
10 Our questionnaire asked respondents about "the range
of offers (9 month compensation)" made to candidates.

We also collected data on summer support and other
support such as signing bonuses or special research funds.
We found no schools offering signing bonuses in our
sample, and no variation across schools in the amount of
special research funds offered. We thus restrict our
definition of "pay" to include 9-month salary plus summer
support.
11 Wj could be directly a positive function of nj; as well;
that is, that a school gets extra utility out of successfully
hiring a highly sought-after candidate. Intuitively this
would increase both the probability of an offer to, and
the pay offered to, a candidate believed to be very popular
in the market, but would not qualitatively change other
model predictions.
12 The assessment of the value of nj could conceivably
also be modeled not as a separate variable, but as a
function of research and teaching potential: school i might
think that higher research and/or teaching potential
candidates are likely to get more offers. Making this
assumption would only strengthen our comparative-static
predictions below. We therefore retain the exogenous
interpretation of nj in the present model.
13 This is simply the probability that with nj independent
draws from the distribution, none would produce a utility
for candidate j higher than Vi. See, for example, the
discussion of order statistics in Mood, Graybill, and Boes
14 We assumed that the school had a policy of offering
the same salary to all candidates who got an offer. It was
described too sensitive to ask the actual salary offered to
each candidate.
15 The probability of an offer is given by exp(Z)/
[1+exp(Z)], where:
Z = 4.97 + 0.35 * RESPOT + 0.14 * TCHPOT + 0.21 * FIT.
16 This could be viewed as a rough proxy for the pressure
schools face to keep up with current market values for
rookie professors, while minimizing salary compression
in their own institutions (which might be more severe at
publicly-funded schools). To quote one colleague at a
public school: "Administrators try to walk a fine line
between paying market prices and making salary
compression worse."
17 Indeed, it was clear in the collection of data on summer
support that there was literally no variation in payments
to rookies on this dimension. This increases our comfort
level with the equal-pay assumption.