Using choice experiments and latent-class modeling to investigate and estimate how academic economists value and trade off the attributes of academic positions*

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Abstract

We investigate how economists would choose among academic positions as a function of the levels of attributes such as department rank, their teaching load, and their salary. We identified all 1735 faculty in the top fifty economics departments and asked each five "Would you prefer to work in Department A or Department B," questions." A latent-class choice model was estimated, indentifying four classes; only average cites/year influence choice.What is preferred and the rates at which attributes substitute for attributes, and for money, vary substantially across the four classes. The largest two classes made choices consistent with *homo economicus*.

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1 Introduction

Our population of interest was faculty members at the top fifty economics departments in the United States. Our goal was to investigate how academic economists would choose among faculty positions as a function of the levels of attributes such as department rank, teaching load, and salary. And, rather than assuming identical preferences, estimate the choice heterogeneity. A second goal was to investigate heterogeneity in the decision rules academic economists use to answer hypothetical choice questions, investigating, for example, the proportion of respondents whose choices appear inconsistent with the neoclassical paradigm.

We identified 57 departments in the top fifty based on the rankings in Dusansky and Vernon (1998), US New and World Report (2001), and Kalaitzidakis et al. (2003).

For academic year $2001 - 2002$, we identified all 1735 faculty in these 57 departments and each was asked, by email, to take a personalized web-based survey, 569 complied.

The primary data used here were each respondent's answers to five pair-wise choice questions: "Would you prefer to work in Department A or Department B?" After each choice question, randomly selected respondents were asked whether they preferred their current position (the status quo), or the alternative just chosen. Table 1 is a choice question from the survey. (All dollar amounts are 1993 dollars, multiply by 1.22 to convert to 2011 dollars)

Table 1: Would you prefer to work in Department A or Department B?

	Department A	Department B
Department's overall rank	11-15	31-40
Department's rank in *{individual's field}*	51%-75%	51%-75%
Your teaching load	2 courses per year	2 courses per year
Seminar series	3 seminars a week none in your field	3 seminars a week none in your field
Your academic salary	\$110,000	\$110,000
Average salary for *{individual's rank}* in the department	\$95,000	\$90,000
	Work in Dept. A ☐	Work in Dept. B ☐

Would you prefer the position and department you choose
or your current position?
☐ I prefer my current position
☐ I prefer the position I chose

Selected position attributes are the department's overall rank, its rank in the individual's field, how many courses the individual will teach, the frequency of seminars (both general in the individual's field), the individual's $Salary$ in that department, the average salary in that department for the individual's rank, and whether the position is the individual's current position. Assistant professors were asked to answer the choice questions assuming they were associate professors with tenure; this was done so the probability of getting tenure in the different departments would not influence choice; assistant professors were not asked the follow-up question.

A latent-class choice model was chosen to estimate the behavioral heterogeneity

We use the pair-wise choices to estimate a choice and choice heterogeneity model of academic position as a function of the levels of the attributes in the two positions, and estimate how much of the choice heterogeneity, if any, can be explained in terms of observable characteristics of the individual. Our choice data are discrete, and there are many ways to incorporate choice heterogeneity into a discrete-choice random-utility model (continuously distributed random parameters, characteristics of the individual deterministically interacted with position attributes, latent-class models, and combinations of these).

The latent-class model – a generalization of the multinomial logit model – assumes the population consists of C latent classes: C is estimated, class membership is latent from the perspective of the researcher, not the individual, and the probability that an individual belongs to class$c$ is estimated as a function of characteristics of the individual (*covariates*).[1] Explaining our choice, our experience is that most individuals naturally tend to lump people into distinct groups, based on their behavior and statements, and the classes are a convenient way to characterize the heterogeneity.

Latent-class choice models are common whenever the goal is to model choice heterogeneity: there are many applications in marketing, transportation, health economics, and environmental economics.[2]

Preferences and the *decision process* are allowed to vary by class. Choosing one's most preferred bundle is one possible decision process, another is answering randomly, and a third is using a heuristic such as choosing based on only a few of the attributes – "attribute nonattendance."[3] A research question is what proportion of economists choose their preferred alternative when presented with a hypothetical choice. Latent-class modeling can inform this question in that it can identify a class or classes whose members behaviors appear economically rational, or irrational, or arbitrary, or simply weird.

Since the number of classes is estimated, latent-class models can flexibly exhibit many forms of choice heterogeneity. Latent-class models can be viewed as mixtures of discrete distributions where the number of discrete distributions is estimated, so quasi non-parametric.

Previewing the results

Our estimated latent-class model has four latent classes: an attribute that is a good (more preferred to less) for one class is sometimes a bad for another class, and the rates at which attributes substitute for attributes, and for money, vary substantially across the four classes. For example, the point estimates imply that if an academic is in Class1 making $\$86K$ he would pay $\$5K$ to reduce his teaching load from 4 to 3 courses but he would have to be paid $\$12K$ to accept an increase from 3 to 4 courses. In comparison, the estimates for an academic in Class1 making $\$160K$ are $\$28K$ and $\$40K$. And, for an academic in Class2 that is currently making $\$160K$, the comparable estimates are $\$18K$ and $\$18K$.

An important finding is that average $cites/yr$ is the only significant determinant of class-membership; or, said the other way, gender, age, and rank explain

[1] See, for example, Laird (1978), Kamakura and Russell (1989), Wedel and Kamakura (2000), and Hagenaars and McCutcheon, eds. (2002).

[2] There are hundreds of examples including Provencher, Baerenklau and Bishop (2002); Greene and Hensher (2003); Scarpa and Thiene (2005); and Breffle, Morey and Thacher (2011).

[3] A difficulty is distinguishing between a respondent that truly does not care about the level of an attribute (indifference) and a respondent that cares but, to simplify the task, ignores the level when making choices. See Hensher (2006) and Cambell, Hensher and Scarpa (2011).

none of the choice heterogeneity over academic job characteristics.[4]

We also estimated a one-class model (a logit) model. It indicates that the *representative* academic economist wants to be in a top-ranked department, teaching as little as possible, with a big *Salary*. The representative academic's parameter estimates are consistent with utility-maximizing behavior. But, the four-class model is more interesting, and statistically dominates the one-class model.

Previewing decision rules

In the four-class model, while the largest two classes make choices consistent with the assumption that academics have well-defined preferences over position attributes and choose the preferred position; it is not clear that the choices of Class3 (19% of the population) conform to these tenets.

How the different classes behave differently, and what is producing these differences, can be considered on many different dimensions: a neoclassical perspective, psychological and behavioral perspectives, whether all respondents are answering the choice questions asked, and the hypothetical nature of the choice questions.[5] We are not wedded to a particular perspective, so typically do not take sides. We mention, sometimes, how different perspectives might interpret our estimates.

For example, we find that most respondents have a strong preference for the *StatusQuo*, but Class4 has a strong preference against the *StatusQuo* (ceteris paribus, they choose the *StatusQuo* (their home department) with low probability). Speculating on the why of a positive *StatusQuo* effect, possible reasons include (1), an endowment effect (a behavioral/psychological motivation (Thaler 1980)); (2), Because choice was hypothetical the respondent has little invested in the answer, so goes, when he can, with the default/simplest choice, the *StatusQuo*; and (3), The home department likely has attractive levels of omitted attributes such as local employment opportunities for spouse.

Alternatively, a negative *StatusQuo* effect (Class4), might be because those in Class4 feel they are not being treated fairly, so want to leave − fairness being an omitted department attribute − or simply because they like change ('the grass is always greener').

Section 2 reviews the literature on how individuals trade-off specific job attributes. Section 3 presents the latent-class model, with the logit model (a one-class model) being a special case. Section 4 discusses the data collection effort and the data. Section 5 presents and discusses the estimates for the one-class logit model; Section 6 presents and discusses our estimated four-class latent-class model; and Section 7 concludes.

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[4] "In your career, approximately how many times have you been cited in the published literature?" Possible answers: 0, $1-10$, $11-50$, $51-100$, $101-200$, $201-500$, $501-1000$, more than 1000. *cites/yr* is your answer divided by the number of years since you received your Ph.D.

[5] In our view, assuming that everyone always answers every hypothetical question arbitrarily is unreasonable, and also unreasonable to assume that individuals always choose their preferred alternative when the choice is binding.

2 There is no literature that models and estimates how academics trade-off specific job attributes

There is research on the academic job market and some on academic economists in particular, but none that models and estimates how academics trade-off the particular attributes of academic positions, or how they trade-off position attributes for salary.[6]

2.1 Job satisfaction surveys of academics

COACHE (the Collaborative on Academic Careers in Higher Education, based at Harvard) has undertaken a number of job satisfaction surveys of academics. One of COACHE's primary goals is researching the recruiting and successful retaining of female and minority faculty, so they have concentrated their survey efforts on untenured faculty asking questions related to bias, fairness and mentoring. (Trower and Bleak 2004a,b and Trower 2010). Summarizing, among the untenured faculty at research universities, females have less job satisfaction than males, and all feel underpaid, but females feel more underpaid.

Relevant to the StatusQuo effect, "COACHE data show that a relatively small percentage (13 percent) of pre-tenure faculty report they will likely leave their institution after achieving tenure there ..." (Helms 2010, 6).

Recently COACHE has started surveying tenured faculty (Trower 2011),

finding that when asked "the number one thing that you, personally, feel your institution could do to improve your workplace," the most common response was "increase salaries." Satisfaction with salary is low amongst full professors and even lower amongst associate professors. The survey did not find a significant difference in salary satisfaction between tenured men and women.

"The second most frequent response to the question, 'If you were to leave your institution, what would be your primary reason?' was 'to improve salary and benefits;' number one was 'to retire.' For those who sought and received outside offers, the number one adjustment to stay put was a salary increase" (Trower 2011). Associate professors are less satisfied with "Department quality" than are full professors.

2.2 The compensating wage-differential literature

> "The whole of the advantages and disadvantages of the different employments of labour and stock must, in the same neighborhood, be either

[6] For a review of the literature on the academic labor market, see Ehrenberg (2003 and 2012).

perfectly equal or continually tending to equality. If in the same neighborhood, there was any employment evidently either more or less advantageous than the rest, so many people would crowd into it in the one case, and so many would desert it in the other, that its advantages would soon return to the level of other employments." Adam Smith (1776: 1976 p.111)

This – Adam Smith's theory of the compensating wage-differential – a hedonic approach[7] – suggests one could estimate how an academic economist would trade off position attributes, and position attributes for money, by estimating actual salaries as a function of position attributes, the individual's research quality and potential, characteristics of the individual that interact with the characteristics of where the position is located (environmental amenities, employment opportunities for partner, etc.), and characteristics such as gender and race. However, this approach is fraught with estimation difficulties: omitted variables, measurement errors, timing issues, search costs and other frictions, the non-competitiveness of this labor market, particularly at the higher ranks, and demand effects such as higher ranked departments are higher ranked because they pay higher salaries.[8] "...the paucity of research on the link between compensating differential and observed job attributes is manifest..." (Fernandez and Nordman 2009).[9] We know of no literature using actual salaries that values how academics trade-off specific position attributes such as teaching load, department rank, and seminar availability, and we do not pursue that approach here.[10]

[7] See the theory of hedonic prices as laid out by Rosen (1974 and 1987). Thaler and Rosen (1976) was a first application to compensating wage differentials.

[8] Most data, including ours, show a positive correlation between an individual's actual salary and the rank of their department.

Mincer and Polachek (1974) is a first example of a hedonic wage regression. Felfe (2012) briefly surveys the history of the hedonic wage regression literature.

[9] There is a wage-differential/hedonic wage regression literature on how some groups trade salary for specific job attributes. Felfe (2012), for example, finds that females with children trade lower wages for more flexible work hours and less stress, which "explains", in part, the "motherhood wage gap" – that females with children make less then females without children. No attempt is made to estimate WTP for each of these job enhancements, the emphasis is on whether there is a compensating wage differential. Loosely speaking, the results suggest that women who after childbirth stay with the same employer accept approximately a 10% reduction in their wage rate in exchange for about 7 less hours of work a week.

Fernandez and Norman (2009) find that in the middle of the earnings distribution workers are compensated for poor working conditions such as "working to tight deadlines." Poggi (2007) surveys the empirical literature on the relationship between wages and working conditions.

[10] While our choice experiment assumes away the issue of tenure by asking the respondents without tenure to assume they have tenure, Ehrenberger, Pieper and Willis (1999) – regressing starting salary on the probability of obtaining tenure – find that departments with lower tenure probabilities pay higher starting salaries, holding constant "the quality tier of the institution." They estimate that, on average, a new hire is paid .7% more to compensate for every 10% decrease in the probability of getting tenure, with the percent bump increasing as department rank decreases. They also find that the salaries of tenured associates in a department are inversely related to the probability of getting tenure in that department.

One might view our approach as a wage-differential approach based on hypothetical data, with the choice-experiment format solving many of the estimation issues encountered with actual job data.

There is an extensive literature, both positive and negative, on the issues associated with hypothetical-choice data. Choice experiments, such as our, are widely used in transportation, marketing, health economics, and environmental economics.

2.3 Rationality and homo economicus

There is little research on whether economists behave "rationally," and what does exist studies undergraduate economics majors rather than economists. Hoffman and Low (1983) investigate whether an undergraduate who pursues a Ph.D. in economics makes the decision in a manner consistent with rational earnings-expectations. They conclude that, on average, they do, but they do not consider the possibility that a subset chooses in a manner inconsistent with rational expectations.

Related, but different, there are been a number of experiments using ultimatum and prisoners' dilemma games that investigate whether economics majors act more selfishly, less cooperatively, than do other undergraduates, and most experiments find that they do.[11] For us, the issue is whether these findings suggest either rationality or irrationality on the part of economists. The answer would seem to be no, unless one assumes concern for others and for fairness must be absent from the preference ordering. The results do suggest that if selfishness is the standard human condition, then economics students are more rational.[12]

In these experiments, the payouts are real, not hypothetical, and none of this literature considers the possibility of heterogeneity in the decision process. We have found no literature on whether economists, in particular, choose their most preferred alternative when the choices are hypothetical – that question is investigated here. Some economists have conjectured, sometimes seriously, sometimes not, that rationality implies that one not spend time cogitating over hypotheticals; so if these economists practice what they preach, they would be required to mindlessly answer our choice questions.

[11] See, for example, the experiments by Frank, Gilovich and Regan (1993), and James, Soroka and Benjafied (2001). Frank and Schulze (2000) found that "economics students are significantly more corrupt than others, which is due to self-selection rather than indoctrination." and Bauman and Rose (2000) find that students who choose economics are less generous. However, Laband and Bell (1999) find that economists are more honest and cooperative than political scientists when it comes to paying association dues.

[12] Gordon Tullock is quoted as saying "the average human being is about 95 percent selfish in the narrow sense of the term" (Frank, Gilovich, and Regan 1993).

3 A latent-class model of position choice

The model is a standard latent-class, discrete-choice model with covariates.

Assume the population of academic economists consists of C different behavioral classes, with C unobserved. The researcher observes three types of data for each individual: $\mathbf{y}_i$, $\mathbf{x}_i$ and $\mathbf{z}_i$. The matrix $\mathbf{y}_i$ is individual i's choice data (his or her position choices); the matrix $\mathbf{x}_i$ is the attribute levels of the positions in individual i's choice pairs; and the matrix $\mathbf{z}_i$ is the explanatory characteristics of individual i (his or her *covariates*).

Latent-class models of discrete choice assume that individuals in the same class use the same behavioral algorithm to make their choices. (One possible behavioral algorithm is all individuals have preferences and all choose their most preferred alternative.) Note that latent-class models allow the behavioral algorithm to vary by class, so, for example, all members of Class$v$ can be choosing their most preferred bundle, while all members of Class$w$ are answering randomly.

The response patterns of individuals from the same class are allowed to be correlated with each other but not correlated with individuals in other classes. However, after conditioning on class, all responses are assumed independent, both across choice pairs and across individuals. That is, the correlation is assumed to be completely induced by the latency of class membership.

Observing $\mathbf{x}_i$, $\mathbf{y}_i$, and $\mathbf{z}_i$, and assuming each individual's class is unobserved, the C class likelihood function is[13]

$$L = \prod_i \left[\Pr\left(\mathbf{y}_i : \mathbf{x}_i, \mathbf{z}_i\right) \right] = \prod_i \left[\sum_{c=1}^{C} \Pr\left(\mathbf{y}_i : \mathbf{x}_i | c\right) \Pr(c : \mathbf{z}_i) \right]. \tag{1}$$

$\Pr(c : \mathbf{z}_i)$ is the unconditional probability of belonging to class c as a function of the individual's covariates, his *unconditional class-membership probability.* (The adjective "unconditional" is to distinguish it from his *conditional class-membership probability*, $\Pr(c : \mathbf{y}_i, \mathbf{x}_i, \mathbf{z}_i)$.)

$\Pr\left(\mathbf{y}_i : \mathbf{x}_i | c\right)$ is the probability of observing the individual's responses to the choice-questions asked, conditional on him belonging to class c.

Given the independence assumption,

$$\Pr\left(\mathbf{y}_i : \mathbf{x}_i | c\right) = \prod_{h=1}^{H} \prod_{j=1}^{J} (P_{ijh|c})^{y_{ijh}}. \tag{2}$$

where $P_{ijh|c}$ is the probability that individual i will choose alternative j in choice set h, conditional on being a member of class c. It is a function of $\mathbf{x}_{ih}$. And $y_{ijh} = 1$ if individual i chose alternative j in choice set h, and 0 otherwise.

[13] In what follows, the colon denotes "as a function of" and the notation "$|c$" represents "conditional on being a member of class c."

Assume the utility/attractiveness individual i in class c associates with alternative j in pair h is

$$U_{ijh|c} = V(\mathbf{x}_{ijh} \left| \boldsymbol{\beta}_{|c} \right.) + \varepsilon_{ijh} \tag{3}$$

where $V(\mathbf{x}_{ijh} \left| \boldsymbol{\beta}_{|c} \right.)$is the deterministic salience of the alternative, conditioned on class. It is a function of the attribute levels of the position, $\mathbf{x}_{ijh}$, and a vector of $\boldsymbol{\beta}_{|c}$ unobserved parameters, which will be estimated.

Assuming ε is Extreme Value distributed, the $P_{Ah|c}$ for the A/B choice pairs is

$$P_{iAh|c} = \frac{\exp(V(\mathbf{x}_{iAh} \left| \boldsymbol{\beta}_{|c} \right.))}{\exp(V(\mathbf{x}_{iAh} \left| \boldsymbol{\beta}_{|c} \right.)) + \exp(V(\mathbf{x}_{iBh} \left| \boldsymbol{\beta}_{|c} \right.))} \tag{4}$$

and the probability of choosing the *StatusQuo* in the follow-up choice question, conditional on class, is

$$P_{iSQh|c} = \frac{\exp(V(\mathbf{x}_{iSQh} \left| \boldsymbol{\beta}_{|c} \right.))}{\exp(V(\mathbf{x}_{iAh} \left| \boldsymbol{\beta}_{|c} \right.)) + \exp(V(\mathbf{x}_{iBh} \left| \boldsymbol{\beta}_{|c} \right.)) + \exp(V(\mathbf{x}_{iSQh} \left| \boldsymbol{\beta}_{|c} \right.))} \tag{5}$$

The *unconditional class-membership probabilities* are specified as

$$\Pr(c : \mathbf{z}_i) = \frac{\exp(W(\mathbf{z}_i \left| \boldsymbol{\gamma}_{|c} \right.))}{\sum_{d=1}^{C} \exp(W(\mathbf{z}_i \left| \boldsymbol{\gamma}_{|d} \right.))} \tag{6}$$

The goal – given $\mathbf{y}_i$, $\mathbf{x}_i$ and $\mathbf{z}_i$ – is to find estimates of the parameters C, $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$.

The model is completed by specifying specific functional forms for $V(\mathbf{x}_{ijh} \left| \boldsymbol{\beta}_{|c} \right.)$ and $W(\mathbf{z}_i \left| \boldsymbol{\gamma}_{|c} \right.)$. The $V(\mathbf{x}_{ijh} \left| \boldsymbol{\beta}_{|c} \right.)$ function is assumed linear and additive in the attributes such that if attribute k is a numerical attribute the additive term is $\beta_{k|c}(x_{ijhk})$, and if x_{ijhk} is a nominal variable the additive terms is

$$(\beta_{k1|c}(x_{ijhk1}) + \beta_{k2|c}(x_{ijhk2}) + ... + \beta_{kM|c}(x_{ijhkM_k}))$$

where $x_{ijhkm} = 1$ if in alternative j, choice-pair h, the attribute level is category m (zero otherwise). M_k is the number of categories of nominal attribute k. Most of our attributes are nominal, so for each c there will be a different parameter estimate for each category of attribute k, one fixed for identification.

The specification of $W(\mathbf{z}_i \left| \boldsymbol{\gamma}_{|c} \right.)$ is parallel to the specification of $V(\mathbf{x}_{ijh} \left| \boldsymbol{\beta}_{|c} \right.)$, but in terms of the covariates instead of attributes, and class-specific $\gamma_{0|c}$ constants. If there is two covariates, and both are continuous

$$W(z_i \left| \boldsymbol{\gamma}_{|c} \right.) = \gamma_{0|c} + \gamma_{1|c} z_{1i} + \gamma_{2|c} z_{2i}$$

with $\gamma_{0|1}$, $\gamma_{1|1}$ and $\gamma_{2|1}$ set to zero for identification.

3.1 Income effects

The continuous attribute *Salary* gets special treatment in $V(\mathbf{x}_{ijh}\left|\boldsymbol{\beta}_{|c}\right.)$ because we feel that it is critical to introduce *income effects*: allow the marginal utility of *Salary*, MU_S, to vary with the level of *Salary*. We incorporate income effects by allowing the salience of *Salary* to "step" down, or up, as it crosses *Salary* thresholds. Specifically we split salary into four categories (in 1993$): the amount $\leq$ \$86K, the amount between \$87K and \$107K, between \$108K and \$140, and the amount over \$140K. We assume the marginal utility is a constant within each category, but allow it to vary across categories.[14]

Specifically, we assume the direct utility from *Salary*, S, is the discontinuous function

$$\begin{aligned} V(S\left|\boldsymbol{\beta}_{s|c}\right.) &= \beta_{s1|c} * (if(S > 86, 86, S)) \\ +\beta_{s2|c} * (if(S &\leq 86, 0, if(S > 107, 21, S-86))) \\ +\beta_{s3|c} * (if(S &\leq 107, 0, if(S > 140, 33, S-107))) \\ +\beta_{s4|c} * (if(S &\leq 140, 0, S-140)) \end{aligned} \quad (7)$$

where the $\beta_{s|c}$ are the class-specific *Salary* parameters and the if statements are in the Excel convention; for example, the third *if* statement

$$(if(S \leq 107, 0, if(S > 140, 33, S-107)))$$

says "if $S < 107$, the term in the parentheses is 0, if $S > 144$, it is 33, and otherwise it is $S - 107$" – it is the amount of *Salary* between 107 and 140. In Eq. 7 it is multiplied by $\beta_{s3|c}$, the marginal utility of *Salary* in this range.

The step specification was chosen because (1), it is a simple way to incorporate income effects; (2), with steps it is easy to estimate money measures of utility changes – typically difficult with continuous income effects; and (3), the specification has worked well for us in the past.[15]

The incorporation of income effects means that willingness-to-pay for a preferred teaching load will vary with *Salary*, as expected, and that WTP to reduce your teaching load from 4 to 3 courses will not necessarily equal, in absolute terms, how much you would have to be compensated to voluntarily increase your load from 3 to 4 courses. (Of course, the model allows for the possibility that a course reduction can be a good or a bad, and allows this to differ across category levels and classes.)

[14] The step points were chosen by looking for natural gaps in *Salary* and by estimating the model with different numbers of steps.

[15] For the difficulties associated with calculating expected compensating and equivalent variation in the presence of income effects see McFadden (1999), Morey (1999), and Dagsvik and Karlström (2005). For step examples, see Morey, Sharma and Karlström (2003) and Morey and Rossman (2008).

Note that the specification allows the marginal utility of *Salary*, in any segment, and any class, to be negative ; positivity is not imposed.[16] In latent-class models, negative income parameters often occur in one or two of the smaller classes. Below we speculate on why this occurs. Note that allowing elements of $\boldsymbol{\beta}_{s|c}$ to be negative is one way to identify choice behavior inconsistent with neoclassical theory.

3.2 The logit model is a special case

Note that if $C = 1$ the model collapses to a simple logit model with step income-effects, and this is the estimated model we report first.

4 The data

For each of the 1735 faculty in the top 57 departments, we complied institution, academic rank, and email address.

From public records, academic year $2001 - 2002$ individual *Salary* data was obtained for 602 faculty at 23 public schools. In addition, we conducted a survey of department chairs in January 2002. This e-mail-based survey asked each chair to provide the most current average *Salary* data by faculty rank. Thirty-two of the department chairs provided at least one of the three averages: 21 chairs (68%) at public universities/colleges and 11 (42%) at private universities/colleges. In the faculty survey, 514 respondents also answered the *Salary* question. Thus, we have actual *Salary* or *Salary* by rank and department for most of the 1735 faculty. To put *Salary* in perspective to today, in $2001 - 2002$, the average salary for the 602 academics with salaries in the public record was $\$73K$ for assistants, $\$83K$ for associates, and $\$120K$ for full professors.

Each of the 1735 faculty was asked by e-mail to take a personalized, web-based survey. The e-mail provided a link to the survey and an individual-specific password so that survey responses could be melded with data on the individual from other sources. Standard sampling protocols were followed.

The faculty survey, in 2002 and early 2003, collected information on research productivity, attitudes, perceptions, characteristics of the individual and his household, current salary, **and** choices over the hypothetical academic positions.

[16] When income effects are assumed away, a one-class model (a logit model) almost always estimates a positive marginal utility of money. When heterogeneity is modeled with continuous distributions, the issue of a negative marginal utility of money is typically restricted away by either admitting no heterogeneity on the money parameter, or restricting the parameter to take only positive values. For example, in random-parameters models the single money parameter is often assumed to have a log-normal distribution. If in a random-parameters model ones assumes the money parameter is normally distributed, one will often find that a significant proportion of the sample has a negative marginal utility of money. Because of this, normality is typically not assumed.

Details on the choice design are available from the authors. In the design, salary was denominated as one of seven percentage shifts from the respondent's current salary.

Five hundred and sixty-nine individuals answered our choice questions, for a choice-question response rate of approximately 33%. That is, we have choice data for 33% of the **population**. Except for assistant professors being marginally overrepresented, the sample appears representative of the population.[17] The data set has answers to 3645 choice questions.

Ignoring for a moment the choice data, the attitudinal data demonstrate that there is significant preference and choice heterogeneity over the attributes of economic positions. The "ideal" number of courses taught per year goes from zero to six; 53% would choose to teach two courses a year, 19% three courses, and 4% would choose one course. (Interestingly the average ideal teaching load does not vary by gender, department rank or professional rank, and this is consistent with what we find in the choice data.) Fifty percent of respondents feel department rank is more important than their field's rank, 18% feel field rank is more important, and 27% think them "equally important." With respect to teaching versus research, only 4% of the sample said they preferred teaching to research; 60% prefer research and 35% "like them equally."

Forty-five percent feel seminars are "very important," and 45% report they go, on average, once a week, but 18% report that they only "occasionally" attend seminars. Six percent say that seminars are "not very" or "not at all" important.

Statistics on all the attitudinal questions asked, and how they break down by gender, department rank and professional rank, can be found at

www.colorado.edu/economics/morey/faculty/index.html.

A primary product of our endeavor is the data; it is rich in information and we hope others will use it. More individual data (e.g. current *Salary*, position, and research output) could be collected and merged at any point in the future. Of course, confidentiality must be maintained.

5 Estimates for the one-class (logit) model

The one-class model ($C = 1$) restrictively assumes everyone has the same preferences and makes their choices using the same algorithm.

[17] Based on a χ^2 test, assistant professors were more likely to respond. Response rates did not vary significantly by department rank, and, after controlling for professional rank, did not vary by gender.

For the 602 academics with salaries in the public record, 202 of these 602 individuals completed our survey (1/3), so public-university academics were no more or less likely to respond than private-university academics. For respondents from public universities, the averages of their published salaries were \$73K for assistants, \$79K for associates, and \$124K for full professors, so close to the population averages.

Estimation is with the software Latent Gold Choice (Vermunt and Magidson 2005). It searches for the $\boldsymbol{\beta}$ parameters that maximize Eq. 1 (with $C = 1$), first using the EM algorithm and then the Newton-Raphson algorithm.

Column 1 of Table 2 (place here) includes a complete list of the nine attributes used in the choice model. Most are self-explanatory. $StatusQuo = 1$ (zero otherwise) for the individual's home department in the follow-up choice question. $Salary40\%Low = 1$ (zero otherwise) if the the $Salary$ the individual sees in an alternative is at least 40% less than the average $Salary$ in that department for his professional rank, and $Salary50\%High = 1$ if the the $Salary$ the individual sees in an alternative is at least 50% higher than the average $Salary$ in that department for his professional rank. These Low and $High$ attributes are designed to pick up attraction or distaste for a salary much high or lower than one's peers.

Table 2 reports the 25 parameter estimates for the one-class model, along with Wald statistics, their associated p-values, measures of each attribute's *importance* and *ceteris paribus (c.p.) probabilities* (a transformation of the parameters into estimated probabilities). $R^2 = .35$, where the baseline is each alternative equally likely, independent of their attribute levels. Assuming the alternative with the highest probability is chosen, the model correctly predicts 75% of the choices, 74% of the A/B choices, and 79% when the $StatusQuo$ is an alternative.

Based on a likelihood-ratio test, the null hypothesis that the marginal utility of $Salary$ is a constant (no steps) is rejected.

The Wald statistics are by attribute and test the null that all the parameters for that attribute are zero. Based on a p-value criteria of .01, one attribute, $Salary40\%Low$, was excluded from the reported logit model. (Looking ahead, it is a significant attribute in the four-class model reported below.)

Importance is a measure of the relative importance of each attribute to choice. $Salary$ is the most important determinant of choice, teaching load is second, and number of seminars in respondent's field is least important.

For each nominal attribute, the *c.p .probability* for category m of attribute k is the probability that an individual would choose category m of attribute k, holding constant the levels of all of the other attributes. For example, the estimated c.p. probability for teaching four courses is .10, meaning that, ceteris paribus, 10% of academic economists would choose, if they could, to teach four courses; 40% would choose one course. Another name for c.p. probabilities are *part-worths.*. They are a useful way to convey some of the information embedded in the parameters.

The one-class parameter estimates, and their implications, are consistent with the standard neoclassical assumptions of choice so the representative academic economist appears as *homo economicus*. Looking ahead, allowing for behavioral heterogeneity results in less conventional but more interesting results.

Interpreting the one-class model, the marginal utility of $Salary$ is always positive, and declines in steps from .08 to .02, a four-fold drop, implying that money measures of attribute changes (department rank, teaching load, etc.) will vary, approximately four-fold, with *Salary* level.

The negative $Salary50\%High$ parameter, $-.40$, indicates that holding your *Salary* constant, you would prefer that it is not way higher than what your peers are paid. It might have had a positive sign.[18]

Less teaching is preferred to more: 40% would choose to teach only one course; 29% to teach two courses, and only 4% would choose to teach five. Higher ranked departments (general and field rank) are, ceteris paribus, preferred to lower-ranked departments. Ceteris paribus, 50% would choose a top ten department and only 12% would choose a $31 - 50$ department.[19]

Given the choice between two equal positions where your department is one of the alternatives, 71% would choose their home department. A preference for the *StatusQuo* shows up in many choice experiments, and a question is why. Our parameter estimate on *StatusQuo* is insensitive to estimating the model with one or more of the other attributes omitted, suggesting *StatusQuo* is an endowment effect, something individuals are endowed with that makes them partial (or adverse) to their current situation, whatever its attribute levels. We tested whether the parameter on *StatusQuo* might vary as a function of characteristics of the respondent. We found no significant *StatusQuo* shifters (a characteristic of the individual interacted with *StatusQuo*). We considered many, including gender, age, years since the Ph.D., professional rank, different measures of family composition, and whether the respondent was attracted to their current position because of the location was a "good place to raise kids" or because of "employment opportunities for significant other."

Seminar activity, while being a significant attribute, is last in importance. Interestingly, more than two general seminars a week is a bad; two is preferred to one but three or more is worse than one. This is reasonable, particularly if an individual feels obligated to show up at most seminars; such feelings of obligation might explain why three seminars ($-.19$) are worse than four or more ($-.05$): if there are four or more, no one is expected to be at all of them.

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[18] Holding his *salary* constant, an individual might dislike a relatively high *Salary* because he thinks it makes it more likely others will get more of future raise pools, or because he views it as unfair or embarrassing. Alternatively, he might like a high relative *Salary* because it signals his importance.

[19] Note that many respondents are choosing departments that are not a real-world option for them – most of us are not top-ten material. This suggests that many of the respondents are answering the question asked, a choice question about their preferences, rather than answering a question about what is feasible.

5.1 Estimated compensating variations for changes in attribute levels – the logit model

Consider the expected compensating variation individual i associates with a change from a position with attribute vector $\mathbf{x}^0$, the initial state, to a position with attribute vector $\mathbf{x}^1$, the new position. An individual's compensating variation for this change, $E[CV_i]$, is how much money has to be subtracted from the individual's *Salary* in the new position to make them indifferent between the new position and the initial position. If $\mathbf{x}^1 \succ \mathbf{x}^0$ (the new position is preferred to the initial position), and if marginal utility of *Salary* is positive for all four steps, as ours are in the one-class model, then $E[CV_i] > 0$. In explanation, a positive amount has to be subtracted from *Salary* to make the individual indifferent between the two two positions. And, if $\mathbf{x}^0 \succ \mathbf{x}^1$, $E[CV_i] < 0$

The estimated $E[CV_i]$ for attribute changes are a way to summarize, in dollars, the information embedded in the parameter estimates; whether the reader believes in their exact cardinal magnitudes is another matter. Some might, for example, believe the dollar estimates are meaningful relative to each other, but that they are all inflated in absolute terms because of the hypothetical nature of the choice pairs.

The step-income-effects specification, since it introduces *income effects*, implies that the $E[CV]$ for a change from $\mathbf{x}^0$ to $\mathbf{x}^1$ will depend on the individual's initial *Salary*, S^0, and that the $E[CV]$ for a change from $\mathbf{x}^0$ to $\mathbf{x}^1$ will not always equal minus the $E[CV]$ for a change from $\mathbf{x}^1$ to $\mathbf{x}^0$.

While our step-income-effects specification is a reasonable and simple way to incorporate income effect, it makes the calculation of $E[CV_i]$ awkward because the act of compensating changes, discontinuously, the marginal utility of *Salary*. Eq. 7, above, makes it difficult to write down a general and usable functional form for $E[CV]$.

That said, with step-income-effects, once the steps are specified and the *Salary* parameters estimated, it is simple to numerically approximate the $E[CV_i]$ for any change in position attributes and any *Salary* level. The footnote explains how and links to an Excel file that does the calculations.[20]

[20] We have not seen this technique used before.

For the one-class model, the Excel file to approximate the $E[CV]$ for any utility change, "oneclassmodelexcelcv.xlsx" is at

www.colorado.edu/economics/morey/faculty/oneclassmodelexcelcv.xlsx

This spreadsheet can be used to approximate $E[CV_i]$, to the nearest $\$1K$, for any change in academic attribute levels. First use the parameter estimates (Table 2) to determine how much the attribute change will change utility, $U(\mathbf{x}^1) - U(\mathbf{x}^0)$, where $\mathbf{x}^0$ is the initial attribute vector (excluding *Salary*) and $\mathbf{x}^1$ is the new attribute vector. (For example,for a teaching load reduction from 4 to 3 courses, $U(\mathbf{x}^1) - U(\mathbf{x}^0) = .51 > 0$ $(-1.33$ to $-.82)$. Then use $U(S) - U(S-1)$, column G, in the Excel file, to determine how much *Salary* has to decrease or increase to offset the utility change; $U(S) - U(S-1)$ is how much utility changes if *Salary* is reduced by $\$1K$ from S. The first column of the Excel file is *Salary*, increasing in $\$1K$ increments from $\$50K$ to $\$200K$, and column F is the direct utility from each *Salary* level (Eq. 7).

Some examples: As noted above, reducing the course load from 4 to 3 courses increases

For example, for someone whose current *Salary* is \$110K the estimated $E[CV]$ for reducing their teaching load from 4 to 3 courses is approximately \$10K, and the estimated $E[CV]$ for increasing their load from 3 to 4 courses is between $-\$13K$ and $-\$14K$. Alternatively, for someone whose current *Salary* is \$85, the estimated $E[CV]$ for reducing from 4 to 3 is \$6K. It would be \$26K if *Salary* were \$169K, a four-fold difference because of the four-fold difference in the marginal utility of initial *Salary*.

Recruiters might estimate the cost of attracting someone from another department. First, they have to overcome the *StatusQuo* effect Ceteris paribus, utility is reduced by .87 if the individual moves to a new department. For someone currently making \$100K, to compensate them to move to an identical department in terms of attributes, would require a *Salary* of \$120K. If their current *Salary* was \$150K, it would require a *Salary* of \$194K. Someone currently making \$120K at a $21-30$ department, all else constant, would require \$40K to move to a $40-50$ department, \$26K for moving, plus \$14K for the rank decrease.

6 The estimated latent-class model

We report a four-class model.

6.1 Determining the number of classes

Models with 1-6 classes were estimated.

There is no classical statistical test to determine whether increasing the number of latent classes significantly improves model fit: a likelihood-ratio test does not exist because the discrete nature of adding a class violates assumptions needed to prove the statistic is Chi-squared distributed (Wedel and Kamakura 2000). In the economic latent-class literature, the number of classes is typically chosen on the basis of *information-criteria scores* – lowest score best.[21] All IC scores are increasing in the number of parameters and decreasing in the estimated likelihood. Numerous information criteria have been proposed – the BIC, AIC, AIC3, and CAIC; they differ in terms of how the improvement in the ln likelihood function is expressed, the form of the penalty function for added

utility by .51. Assume, for example, that $S = 110$, link to the Excel file and go to the G column cell corresponding to $S = 109$ (one less than current *Salary*), highlight this cell and then drag the pointer up the vertically adjacent cells until the sum of the contents of the highlighted cells approximates .51. Rounding this requires 10 cells, so the estimated $E[CV]$ is 10 cells, approximately \$10K. Alternatively, if courses are increased from 3 to 4 courses, the utility change is $-.51$ and $E[CV]$ is approximated by highlighting the G cell corresponding to $S = 111$ (one more than current *Salary*) and then dragging the pointer down the vertically adjacent cells until the sum of the contents of the highlighted cells approximates .51. This will require between 13 and 14 cells, so $E[CV]$ is between $-\$13K$ and $-\$14K$.

[21] In education and psychology, the practice is to first find the minimum number of classes that produce a "good fit" in terms of actual versus predicted responses. Information criteria are then used to examine the trade-off between parsimony and fit. As reported below, our four-class model has "good fit."

parameters, and whether the criteria is a function of the sample size.[22] The BIC criteria is the most conservative criteria in that it penalizes the most for additional parameters. It indicates 3 or 4 classes (their BICs are effectively equal). Three classes is better than four based on the CIAC criteria, and four is better than three based on the AIC and AIC3 criteria.[23] The heterogeneity in the four-class model is more interesting. All that said, the answer to "how many classes?" is somewhat arbitrary and often purpose driven, coming down to how finely the researcher wants, or needs, to parse the heterogeneity.

6.2 The four-class model

Our four-class model has 101 estimated parameters. It restricts the parameters on one attribute, $GenSem$ (the number of general seminars a week), to not vary by class because one cannot reject the null hypothesis that it does not vary by class.

Both $Salary40\%Low$ *and* $Salary50\%High$ are significant determinants of choice; $Salary40\%Low$ was not significant in the one-class model.

This best four-class model has only one significant covariate, $cites/yr$. (Looking ahead, Table 7 reports estimated $\Pr(c : cites/yr_i)$ for different levels of $cites/yr$.)

We estimated models testing the following variables as covariates (determinants of class membership): $cites/yr$, gender, age, years since the Ph.D., professional rank, self-reported Asian, self-reported Hispanic, different measures of family composition, life-time citations, articles published in the last three years, and whether the respondent was attracted to their current position because the location was a "good place to raise kids" or because of "employment opportunities for significant other."[24] That none of these was a significant covariate is both important and somewhat surprising;[25] while there is significant behavioral heterogeneity, it is not explained in terms of characteristics of the respondents, or at least not in terms of the many we measured.

Having only one covariate makes it difficult to discriminate between different hypotheses about why an individual is in the class they are in, other than saying the results provide no support for explanations that would be supported if a particular variable has been found to be a significant covariate. For example,

[22] For details on, and comparisons of, the different information criteria, see Akaike (1974), Bozdogan (1987), Hurvich and Tsai (1989), Schwarz (1978) and Yang and Yang (2007).

[23] Andrews and Currim (2003) and Dias (2004) suggest that in choice models AIC3 is a better criterion than the BIC or AIC.

[24] Only two individuals in the sample self-identified as Black.

[25] Covariates enter via Eq. 6. The significance of each potential covariate was tested by estimating a separate four-class model with each potential covariate. (.01 was the chosen significance level.) In addition, models were estimated with *cites/yr* as a covariate, adding, one at time, the other potential covariates. *cites/yr*, by itself, is a significant covariate and *cites/yr* always remained significant if another potential covariate was added. While a few of the other potential covariates were, by themselves, significant at .01, none were significant when *cites/yr* was included. The significance of covariates was also investigated with three and five-class models.

if we had found that those checking that the location of their department is "a good place to raise kids" increased the probability that they belonged to a class that mostly chooses the *StatusQuo*, it would have added support to the argument that the *StatusQuo* effect is driven by omitted variables rather than a psychological endowment effect. But, current department being a "good place to raise kids" is not a significant covariate. Additional support for the *StatusQuo* effect being an endowment effect was presented in the discussion of the one-class model.

The four-class model correctly predicts 86% of the choices, 85% of the A/B choices, and 92% of the choices when the *StatusQuo* was in play. Overall $R^2 = .64$; by class, the R^2 are, in order .57, .81, .18 and .93. Note how much lower the predictive power is for Class3.

Another dimension of fit is how accurately the model allocates the respondents to classes; which must be estimated because class-membership is latent. For each respondent, there are four estimated conditional class-membership probabilities, the four $\Pr(c : \mathbf{y}_i, \mathbf{x}_i, \mathbf{z}_i)$. Each academic can be assigned to the class associated with his highest conditional class-membership probability (called a *modal classification*). The largest of these four conditional class-membership probabilities is $\geq$ 90% for 43% of the respondents, and $\geq$ 70% for 69% of the respondents. At the other extreme, the largest of these four probabilities is less than 50% for only for 7% of respondents. The accuracy of the allocation is measured with what is called the *classification error* (Vermunt and Magidson 2005). It compares the number assigned to class c based on the modal classification with the sum, over respondents, of the estimated conditional class-membership probabilities for class c. For example, the modal classification predicts 226 respondents in Class1 and the sum predicts 264, so the classification error for Class1 is $(1-226/264) = 0.14$. In contrast, the classification error for Class3 is 0.28, twice as high. Overall, the sample classification error is .20, suggesting modal classification gets it wrong 20% of the time, not that often.

Table 3 (place Tables 3-6 here) reports the parameter estimates, by class.[26] Table 4 reports *importance* of each attribute by class. Table 5 reports the *c.p. probabilities* for each nominal attribute, and $cites/yr$, by class.[27] And, Table 6 reports the *probability means* for each nominal attribute, by class.

Salary is the most important determinant of choice in all four classes, as in the one-class model, but the importance scores (Table 4) indicate that *Salary* is a much more important determinant of choice for Classes 1 and 2 than it is for Classes 3 and 4. The importance scores indicate that *StatusQuo* and $Salary40\%low$ are much more important for Class3 than they are for the other

[26] One has to be careful when viewing how a single parameter varies across the four classes because there is nothing forcing the same parameter scale for each class. It is the relative values of the parameters within a class and how these relative values vary by class that largely drives the choice probabilities and how they differ by class. For example, Class4 has a salary-parameter estimate for $\leq \$86K$ which is five times larger than the estimate for Class1, but its estimates for other attributes are larger as well.

[27] In the table, the "." under $cites/Yr$ denotes missing values for $cites/Yr$.

Classes.

The *probability mean* is an estimate of the probability that an individual is in class c, given the individual would choose, ceteris paribus, category m for attribute k. For example, if you, ceteris paribus, choose to be in a top five department, there is a 62% change you are in Class1 and only a 2% change that you are in Class4, but if you choose to be in an $11-15$ department there is a 61% chance you are in Class4.

The estimated aggregate class-membership probabilities, the $\Pr(c)$, are .47 for Class1, .21 for Class2, .19 for Class3, and .15 for Class4, so 264 of the respondents are predicted to belong to Class1, and 85 to Class4. Extrapolating to the population of 1735 academic economists, 815 are predicted to be in Class1.

6.3 The different decision processes

Class1 is the neoclasical-consistent, mostly-monotonic-in-attribute class, similar in description to the one-class model, just more emphatically. Higher rank is preferred and less teaching is preferred. The parameter estimates for the representative academic in the one-class model (Table 2) were likely driven by the respondents in Class1, with the choices of the three other Classes softening the one-class estimates. In Class1 the MU_S estimates monotonically decline eight-fold, but only decline four-fold in the one-class representative model. And, in Class1 the parameter estimates on *DeptRank* decline monotonically from zero to -3.33, but in the one-class model the monotonic decline is shortened to -1.65.

Class2, like Class1, is consistent with the tenets of neoclassical theory, but, for Class2, MU_S is U-shaped: each dollar above $\$140K$ brings 35% more utility than does a dollar in the $\$108K$ to $\$140K$ range, but still less than a dollar in the $< \$87$ range. Maybe for members of Class2 there is a prestige bump on *Salary* when it is over $\$140K$, a signal, for them, of their high value.

Class3 is aberrant for economists who study choice, but would not be to a psychologist studying academic economists. First the results for Class3:

- For six of the eight nominal attributes, the c.p probabilities do not vary much across the categories, indicating their levels only marginally affect choice. For example, across the five different course loads the c.p. probabilities (Table 5) are .20, .16, .21, 24 and .19 – little variation compared to the other three classes.

- The two nominal attributes for which category is important are $Salary40\%Low$ (few want it) and *StatusQuo* (strongly prefers it) – note the Class3 importance scores for these two attributes (Table 4).

- *Salary* plays its smallest choice role in Class3 (Table 4), and for Class3 the marginal utility of *Salary* is negative for $S \leq \$86K$ and $S > \$140K$.[28]

[28] As discussed earlier, when one allows for heterogeneity in the marginal utility of money and one allows it to be negative, one often finds it significantly negative for some respondents.

- In addition, Class3 is the only class where an increase in$cites/yr$ decreases the probability of class membership.

The question is what to make of these results. For many of the attributes, Class3 behaves as if they care about the levels of the attributes, but not much – not indifference, but close.

There are at least five possible explanations for Class3:

1. Members of Class3 care about the levels of all or most of the attributes, have relatively homogenous preferences, and don't necessarily prefer the *StatusQuo* but, because of the hypothetical nature of the choice questions, minimize "answer effort" by choosing the *StatusQuo* when a follow-up question is asked, and answer quasi-randomly when an A/B pair is asked.

2. Members of Class3 don't care much about the attribute levels but do have a fondness for their home department, simply because it is their home department (the endowment effect).

3. Members of Class3 care about the attribute levels and each chooses his most preferred position, but lots of different preferences are represented – Class3 is a mixed bag – making Class3 a sort of everyone-not-in-another-class class.

4. Members of Class3 are behaving irrationally in the economic sense of the word.

If you believe more money, ceteris paribus, is always preferred to less, then the two estimated negative MU_s for Class3 are not MU_S estimates, and all estimates derived from them, including estimated $E[CV]$, are uninformative. In which case, these perverse signs must be due to either lack of answer effort, a misunderstanding of the questions, scenario rejection, or a desire to mess up the results. There is no indication that anyone misunderstood the questions or wanted to mess up the results.

Of course all the members of Class3 need not have the same motivations, and not all readers the same beliefs.

A few thoughts with respect to Class3: Our experience with latent-class choice models in environmental applications is that there is often a class that chooses as if they indifferent to the level of environmental quality. This could be because they are unfamiliar with the environmental commodity, or because they reject the clean-up scenario, or because they truly don't care about the quality of the environmental resource in question. While academic economists are familiar with the attributes of positions, some might be uncertain about how they would feel in a different department with different attribute levels.[29]

[29] Uncertainty about how one would feel in a department different from one's own, combined with risk aversion, could generate a preference for the *StatusQuo*, a preference which is not, per sec, an endowment effect.

Or, some academics might, in fact, be indifferent to department attributes: we teach alone and our research often has little to do with our colleagues, so some academics might not care about rankings or seminars. (The first author of this paper claims to not care about *DeptRank*, *FieldRank* or seminar frequency, but behaves as if he cares about teaching load and *Salary*.) Respondents who are less research productive (fewer $cites/yr$) are more likely to be in Class3 and we wonder if this might partially explain choices in Class3 in that those who are less research productive might care less about the research-related attributes of where they work.

For Class3, we question whether members really consider more money a bad when their salary is high or low in absolute terms, suspecting that minimizing answer effort is playing a role. Because Class3 might be the "answer-arbitrarily" class, looking ahead, we assess with caution the sometimes strange, but interesting, $E[CV]$ estimates for Class3.

Critics of hypothetical choice questions often assert "Ask a hypothetical question get a hypothetical answer." Maybe our finding is "Ask an academic economist a hypothetical question and 19% will give a hypothetical answer," with many of the rest answering as if it were a choice with real consequences. If so, are the 19% choosing quasi-randomly because that is the easiest thing to do, or might they be compelled to answer without cogitating because many economists teach it is irrational to expend effort cogitating on a hypothetical, and want to remain true to what they teach? This could be tested by administering the survey to academics who are not economists and see if Class3 shrinks.

Class4, the smallest class, is of one mind (very homogenous) on $Salary40\%Low$, $Salary50\%High$, *DeptRank*, *FieldRank*, *Teach* and *StatusQuo*: examining the c.p. probabilities, no one in Class4 wants a relatively low *Salary*, a relatively high *Salary*, or to stay where they are; everyone wants their new department to be top 10% in their field; 96% would choose to teach two courses, and 97% want to be in a $11-15$ Department. Anyone who would, ceteris paribus, choose a $11-15$ department is likely in Class4 (61% probability mean) even though only 15% of the population is in Class4.

A possible explanation for all of Class4 wanting to be in a $11-15$ department is that Class4 individuals think their research skills and work ethic are commensurate with that rank, and feel that they would be uncomfortable at a higher or lower ranked department. (As we noted earlier, 50% of all respondents would, ceteris paribus, choose a top-ten department, so such discomfort is not universal.)

As noted in the introduction, a reason for a respondent never choosing the *StatusQuo* might be he feels he is not being treated fairly by his home department. The survey asked, "Relative to others in your department, how do you feel you have been treated with respect to yearly raises in the last three years?" with one response being, "I have not been treated fairly with respect to yearly raises." (12% choose this response). It also asked, "Which of the following statements best describes how you feel about your current academic *Salary*?" Thirty-eight percent choose "underpaid" or "grossly underpaid." But, the correlation between being underpaid and the conditional probability of being in Class4 is

.01, and the correlation between "not...fairly" and the conditional probability of being in Class4 is .02, so this is not what is driving Class4 membership.

For Class4, MU_S is positive and declining, except it is negative between $\$108K$ and $\$140K$. The question is what to make of this negative parameter? Our inclination is to think that many in Class4 are purposefully avoiding salaries in the $\$108K$ to $\$140K$ range: the coefficients on the other attributes suggest that they are paying careful attention to the other attribute levels, so it seems reasonable to assume that they are paying attention to *Salary*. The question is why are they are disinclined towards positions with salaries in this range? We do not have a good story. It might be because the respondent considers these salaries "not in line" given the levels of the other attributes – causing them to reject the alternatives with salaries in the $\$108 - \$140K$ range, scenario rejection.

6.4 Class heterogeneity, attribute by attribute:

- Members of Class1 are evenly split as to whether or not they would choose a relatively low or high *Salary*; Class2 always want a *Salary* that is low in relative terms; and Class4 never wants a *Salary* that is extreme in relative terms.
- Class2 all want to teach one course and Class4 all want to teach two courses. As with many of the other attributes, Class3, as a class, seems almost indifferent to teaching load.
- Class4 all want to be in a $11 - 15$ department, and Class2 mostly want to be in a $16 - 20$ department. Class1 is monotonic in *DeptRank*.
- With respect to *FieldRank*: all of Class4 wants to be top 10%.
- All the classes have a strong preference for the *StatusQuo*, except Class4, which would, ceteris paribus, never choose it.
- Recollect that the influence of *GenSem* was restricted to not vary across the four Classes.
- Compared to Class1, members of Classes 2 and 4 are twice as likely to choose one field seminar a week (.80 vs. .40)

6.5 Predicting class membership

You might know an individual, including yourself, well enough to intuitively know to which Class he belongs, but, if in doubt, you can estimate the individual's class-membership probabilities. If you know nothing about the individual, you would use the estimated proportion for each class, the $\Pr(c)$; e.g. .47 for Class1, ... and .15 for Class4. If you observed only the covariate levels for the individual – in our case *cites/yr*– you would use the the individual's unconditional class-membership probability, his $\Pr(c : cites/yr_i)$. Table 7 shows how the $\Pr(c : cites/yr_i)$ vary with *cites/yr*.

Table 7: estimated $\Pr(c : cites/yr_i)$

cites/yr ↓	Class1	Class2	Class3	Class4
0	.43	.16	.29	.12
10	.46	.19	.21	.14
25	.48	.22	.12	.17
50	.47	.28	.04	.21
100	.36	.36	.00	.28

Note how the probability of being in Class3 monotonically declines as *cites/yr* increases, and how the probability of belonging to Class1 is not much influenced by *cites/yr*.

If, in addition, you observed one or more choices for the individual, you could use the individual's conditional class-membership probabilities, his $\Pr(c : \mathbf{y}_i, \mathbf{x}_i, cites/yr_i)$. That is, you could ask the individual to answer a few position choice-pair questions and then use the individual's choices to more precisely allocate the individual to a class. Specifically, for $c = 1, 2, 3, 4$, and three A/B choice pairs:

$$\begin{aligned}\Pr(c \quad : \quad \mathbf{y}_i, \mathbf{x}_i, cites/yr_i) &= \frac{\Pr(\mathbf{y}_i : \mathbf{x}_i | c) \Pr(c : cites/yr_i)}{\Pr(\mathbf{y}_i : \mathbf{x}_i)} \qquad (8)\\ &= \frac{\Pr(c : cites/yr_i) \prod_{h=1}^{3} \prod_{j=1}^{2} (P_{ijh|c})^{y_{ijh}}}{\sum\limits_{d=1}^{4} \Pr(d : cites/yr_i) \prod_{h=1}^{3} \prod_{j=1}^{2} (P_{ijh|d})^{y_{ijh}}}\end{aligned}$$

which, given the parameter estimates, can be calculated for any *cites/yr* and any three choices.

For example, consider the example choice pair, Table 1, and the following two choice questions that did not appear in the survey (Tables 8 and 9). To calculate your $\Pr(c : \mathbf{y}_i, \mathbf{x}_i, cites/yr_i)$, determine your *cites/yr* and answer the three choice questions (Tables 1, 8 and 9).

Table 8: First test example: Would you prefer to work in Department A or Department B?

	Department A	Department B
Department's overall rank	16–20	11-15
Department's rank in *{individual's field}*	26-50%	top 10%
Your teaching load	1 course per year	2 courses per year
Seminar series	3 seminars a week none in your field	3 seminars a week none in your field
Your academic *Salary*	\$100,000	\$110,000
Average *Salary* for *{individual's rank}* in the department	\$100,000	\$90,000
	Work in Dept. A ☐	Work in Dept. B ☐

Table 9: Second test example: Would you prefer to work in Department A or Department B?

	Department A	Department B
Department's overall rank	1-5	16-20
Department's rank in *{individual's field}*	11-25%	51-75%
Your teaching load	2 course per year	2 courses per year
Seminar series	2 seminars a week	2 seminars a week
	1 in your field	1 in your field
Your academic *Salary*	$100,000	$150,000
Average *Salary* for *{individual's rank}* in the department	$150,000	$125,000
	Work in Dept. A	Work in Dept. B
	☐	☐

One can then use, Eq. 8 to calculate your four $\Pr(c : \mathbf{y}_i, \mathbf{x}_i, citesYr_i)$.

For example, if $citesYr = 5$ and you answered A, A, and A, your four conditional class-membership probabilities are .29, .02, .69 and .00, so you are most likely in Class3, the aberrant class. Alternatively if you answered B, B, and B your four conditional class-membership probabilities are .48, .00, .52 and .00, so you are in Class1 or 3. If you answered A, B, A, your four conditional class-membership probabilities are .41, .00, .05 and .55, and you are most likely in Class1 or 4.

Alternatively if $citesYr = 50$, and you answered A, B, A, your four conditional class-membership probabilities are .32, .00, .01 and .67, so you are most likely in Class4. If your $citesYr = 50$ and you want to be in Class2, answer A, A, B.

—

Next, consider predicting for any individual their choice of position over any set of J positions ($J \geq 2$) where each position/department is defined in terms of its attribute levels. You proceed by first estimating the four class-specific choice probabilities for each j (Eq. 3 extended to the appropriate number of alternatives). The choice-probability estimates are the sum of these class-specific estimates, each weighted by the best estimate of the probability that the individual is in that class.

6.6 Estimated compensating variations for changes in attribute levels for the four-class model

One can approximate the $E[CV]$ for each class and *Salary* for any change in attribute levels using the same methodology that was used for the one-class model, but now the estimates are conditional on class. One finds the salary change that makes an individual in class c with *Salary* S indifferent to the attribute change.[30]

[30] An Excel file to do this, "fourclassmodelexcelcv.xlsx"

Note that for a given attribute change, the utility change will be different for each class, and sometimes the attribute change will cause a utility increase in some classes (a good) and a utility decrease (a bad) in other classes.

Before we consider some of these $E[CV]$ estimates, some points should be made and some cautions considered:

1. (1) If the marginal-utility of $Salary$ is always negative in the range in which compensation occurs, the $E[CV]$ will have the "wrong" sign (e.g. $E[CV] < 0$ for a utility increase) because compensating for a utility increase will require that $Salary$ is increased, not decreased.

2. The calculation, and interpretation, of the $E[CV]$ is further complicated, and muddled, if the marginal utility of $Salary$ **switches** signs one or more times. Such switching can cause the following:

   (A) it can cause the magnitude of $E[CV]$ to greatly increase because adjusting $Salary$ might initially move total utility further from the utility level in the original state – one must get past the $Salary$ levels with the "wrong" sign;

   (B) compensation might be achieved by moving $Salary$ in the unconventional direction (e.g. increasing $Salary$ to compensate for a utility increase because eventually more $Salary$ will be a bad);

   (C) an $E[CV]$ might not exist; and

   (D) if the marginal utility of $Salary$ is negative in one or more ranges, whether there is free disposal of $Salary$ becomes an issue. If the marginal utility of $Salary$ is, for example, negative between \$107K and \$140K, but positive above \$140K, and $Salary$ is \$160K, it makes little sense to imagine the disposal of only the amount between 107 and 140. However, if the marginal utility of $Salary$ is negative above \$160, but positive at all lower salaries, whether an academic can throw away $Salary$ above \$160K can become relevant to the calculation of $E[CV]$, and even whether $E[CV]$ exits.

Since in Classes 1 and 2 the marginal utility of $Salary$ is always positive, all their $E[CV]$ estimates are positive for utility increases and negative for utility decreases.

This is not the case for all possible Class 3 and 4 $E[CV]$ estimates. For Class4, care is needed in interpreting $E[CV]$ that require compensation in the \$108K to \$140K range.

The cautions about Class3, stated earlier, should be kept in mind. One might reasonably assume that the $E[CV]$ estimates for Class 3 tell us little

is atwww.colorado.edu/economics/morey/faculty/fourclassmodelexcelcv.xlsx

The file contains four $U(S) - U(S-1)$ columns, one for each class.

about their actual $E[CV]$'s. If so, one might reassign each Class3 individual to what would be his more likely class if Class3 did not exist.

Or, alternatively, one might conclude that members of Class3 simply do not have preferences or $E[CV]$, are not members of the species homo economicus.

Tables 10-13 report the estimated $E[CV]$ for five different attribute changes:

1. a course reduction from 4 to 3 courses;
2. a course increase from 3 to 4 courses;
3. leaving the *StatusQuo* (taking a job at a different, ceteris paribus, department);
4. One's *DeptRank* decreasing from $21-30$ to $41-50$; and
5. One's *DeptRank* increasing from $41-50$ to $21-30$.

The tables report each for four different initial salaries: $\$87K$, $\$110K$, $\$130K$, and $\$160K$.

For Class1 reducing the course load from 4 to 3 courses increases utility by 1.34. If $S = \$110K$, $E[CV]$ is approx. $\$12K$. For increasing from 3 to 4 courses $E[CV]$ is approximately $-\$16K$, implying that a member of Class1 currently making $\$110K$ would pay $\$12K$ to reduce their load from 4 to 3 courses, but would have to be compensated $\$16K$ to voluntarily teach a fourth course.

For Class2 reducing the course load from 4 to 3 courses increases utility by 3.74. If $S = \$110K$, $E[CV]$ is approx. $\$19K$. For increasing from 3 to 4 courses, $E[CV]$ is approximately $-\$19K$; they are equal because no "steps" are crossed in either direction.

For Class4 reducing the course load from 4 to 3 courses increases utility by 8.81. If $S = \$110K$, $E[CV]$ is approximately $\$11K$. For increasing from 3 to 4 courses it is $-\$88K$.

Table 10: Some Class1 estimated $E[CV]$ [31]

	S=\$87K	S=\$110K	S=\$130K	S=\$160K
4 to 3 courses (good)	\$5K	\$12K	\$16K	\$28K
3 to 4 courses (bad)	-\$12K	-\$16K	-\$26K	-\$40K
leave SQ (bad)	-\$18K	-\$24K	-\$45K	-\$61K
21-30 to 41-50 (bad)	-\$13K	-\$17K	-\$29K	-\$45K
41-50 to 21-30 (good)	\$5K	\$13K	\$17K	\$29K

Table 11: Some Class2 estimated $E[CV]$

	S=\$87K	S=\$110K	S=\$130K	S=\$160K
4 to 3 courses (good)	\$8K	\$19K	\$18K	\$13K
3 to 4 courses (bad)	-\$18K	-\$19K	-\$16K	-\$13K
leave SQ (bad)	-\$7K	-\$7K	-\$7K	-\$5K
21-30 to 40-50 (good)	\$5K	\$12K	\$12K	\$9K
40-50 to 21-30 (bad)	-\$13K	-\$12K	-\$11K	-\$9K

[31] Rounded downward to the nearest $\$1K$

Ignore, or not, the estimates for Class3.

Table 12: Some Class3 estimated $E[CV]$

	S=\$87K	S=\$110K	S=\$130K	S=\$160K
4 to 3 courses (bad)	-\$3K	-\$8K	-\$7K	\$18K ("wrong sign)
3 to 4 courses (good)	n.e. or \$253K[32]	\$4K	\$7K	-\$18K ("wrong sign)
leave SQ (bad)	n.e.	n.e.	n.e	n.e.
21-30 to 40-50 (bad)	-\$1K	-\$3K	-\$3K	\$8K ("wrong sign)
40-50 to 21-30 (good)	n.e.	\$3K	\$3K	-\$8K ("wrong sign)

Table 13: Some Class4 estimated $E[CV]$

	S=\$87K	S=\$110K	S=\$130K	S=\$160K
4 to 3 courses (good)	\$7K	\$11K	n.e. or \$40K	\$71K
3 to 4 courses (bad)	-\$9K	-\$88K	-\$59K	-\$30K
leave SQ (good)	\$14K	\$19K	n.e. or \$50K	63K
21-30 to 40-50 (bad)	-\$185K	-\$232K	-\$174K	-\$145K
40-50 to 21-30 (good)	\$33K	\$40K	\$69K	\$100K

7 Summary and conclusions

Our goal was to investigate how academic economists would choose among hypothetical academic positions as a function of department rank, department rank in the individual's field, teaching load, level of seminar activity (both in general and in the individual's field), *Salary*, whether the *Salary* was much higher or lower than the average in the department for the individual's academic rank, and the *StatusQuo*.

For academic year 2001−2002, we identified all the full-time academics in the top fifty economics departments and asked each by email to take a personalized, web-based survey. While much data were collected, the primary data used here were each respondent's answers to five pair-wise choice questions: "Would you prefer to work in Department A or Department B?" And, after each choice question, many respondents were asked whether they preferred their current position, the *StatusQuo*, or the alternative just chosen.

First we estimated a simple logit model of academic choice. It finds that the *representative* academic economist wants to be in a top-ranked department, teaching as little as possible, with a big *Salary*. *Salary* is the most important determinant of choice followed by teaching load and *DeptRank*. There is a strong *StatusQuo* effect: ceteris paribus, the representative academic will choose his home department 71% of the time. Marginal utility of *Salary* declines fourfold, in steps, so there are strong income effects. And, his choices are consistent with him playing homo economicus.

$E[CV]$ are a convenient way to express the differences between the classes – even if one believes the dollar amounts are scaled up, or down, because the

[32] n.e.=nonexistent.

choice questions are hypothetical. Consider the cost of recruiting someone from another department. The recruiter has to overcome the *StatusQuo* effect. Ceteris paribus, estimated utility is reduced by .87 if the individual moves. For someone currently making $\$100K$, to compensate them to move to an identical department in terms of attributes, would require a *Salary* of $\$120K$, the $\$20K$ to overcome the *StatusQuo* effect. If their current *Salary* was $\$150K$, it would require a *Salary* of $\$194K$. Someone currently making $\$120K$ at a $21-30$ department, all else constant, would require $\$40K$ to move to a $40-50$ department, $\$26K$ for moving, plus $\$14K$ for the rank decrease.

This one-class model was then generalized by allowing for latent classes. A latent-class model assumes the population consists of C latent classes, where C is estimated along with the probability that individual i belongs to class c as a function of characteristics of the individual (*covariates*). Preferences and the decision process are allowed to vary by class.

The null hypothesis that there is only one class (the logit model) is rejected. The latent-class model is also more interesting and more revealing. It raises a number of questions about the decision process(es) different academic economists use to answer hypothetical choice questions.

Our latent-class model has four behavioral classes and only one significant covariate, $citesYr$. (We were surprised that characteristics such as gender and "years since Ph.D." were not significant determinants of the class-membership probabilities.) Behavior varies drastically across the four classes, but $cites/yr$ does not explain a lot of that heterogeneity; so, while we identify heterogeneity, we are not explaining most of it. We show that most of the heterogeneity cannot be explained in terms of usual suspects; there are, for example, no gender effects.

The four-class model correctly predicts 86% of the choices. While the largest two classes made choices consistent with *homo economicus*, it is not clear that the choices of Class3 are consistent with the tenets of rational choice.

Class3 (19% of the population) chooses as if they are only marginally care about the levels of many of the attributes. *Salary* plays its smallest choice role in Class3 and for Class3 the marginal utility of *Salary* is negative for $Salary \leq \$86K$ and $Salary > \$140K$. (In choice models that allow heterogeneity in the marginal utility of income, it is not uncommon for a small but significant proportion of respondents to have an estimated negative marginal utility of income, at least in some income ranges.)

Class3 might be behaving irrationally, they might be a mixed bag of quirky preferences, they might simply be answering quasi-randomly because of the hypotheticalness of the exercise. (Economists tend to assume that respondents have well-behaved preferences and choose the most preferred alternative, at least when the choice is real rather than hypothetical – here the choices are hypothetical. With both hypothetical and real choices, our experience indicates that the more heterogeneity admitted (continuous or discrete), the more likely the researcher observes segments of the sample that behave in a fashion that is awkward for the tenets of neoclassical demand theory, and that happens here.)

Describing the classes: Class1 is the neoclasical-consistent, mostly-monotonic-in-attributes class, similar in description to the one-class model, just more so.

Higher rank is preferred and less teaching is preferred.

Class2, like Class1, is consistent with the tenets of neoclassical theory, but for Class2 the marginal utility of $Salary$ is U-shaped. And, ceteris paribus, 68% want to be in a $16-20$ department.

Classes 1-3 prefer the $StatusQuo$, but, ceteris paribus, Class4, will never choose the $StatusQuo$.

Class4 is of one mind: no member wants a relatively low or high $Salary$, or to stay where they are; everyone wants their new department to be top 10% in their field; 96% would choose to teach two courses, and 97% want to be in a $11-15$ department.

An attribute change that is utility increasing for one Class can be utility decreasing for another Class. For example, if an individual's current $Salary$ is $\$110K$ and he is in Class1, lowering his department's rank from $21-30$ to $41-50$ makes him worse off, and he would have to be paid $\$13K$ to be made whole. But, if he is in Class2, the same move is utility increasing and he would pay $\$5K$ to make it happen. Tables 10-13 provide examples of $E[CV]$ for different attribute changes by $Salary$ and by class; those for Classes 3 and 4, particularly 3, need to be cautiously digested. Different readers will put more or less faith in our parameters estimates, but they are, to our knowledge, the only existing estimates of how academic economists trade off position attributes.

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Table 2: four-Class Model Parameter Estimates

	Class1	Class2	Class3	Class4	Wald	p-value	Wald(=)	p(=)value
Salary								
Salary<=86	0.25	0.43	-0.01	1.24	88.75	0.000	76.69	0.000
86<Salary<=107	0.11	0.19	0.03	1.10	67.12	0.000	16.99	0.001
107<Salary<=140	0.08	0.20	0.01	-0.56	111.78	0.000	40.01	0.000
Salary>140	0.03	0.27	-0.01	0.29	53.72	0.000	42.73	0.000
Salary40%Low								
No	0.00	0.00	0.00	0.00	19.21	0.001	19.07	0.000
Yes	0.16	4.27	-1.41	-20.08				
Salary50%High								
No	0.00	0.00	0.00	0.00	23.44	0.000	23.33	0.000
Yes	0.12	-5.80	-0.06	-18.15				
Dept. Rank								
1 to 5	0.00	0.00	0.00	0.00	181.75	0.000	99.06	0.000
6 to 10	-0.11	-1.76	-0.11	-2.66				
11 to 15	-0.86	-4.11	-0.84	3.45				
16 to 20	-1.50	0.96	-0.66	-10.75				
21 to 30	-1.89	-5.59	-0.79	-13.59				
31 to 40	-2.66	-4.88	-0.51	-34.45				
41 to 50	-3.33	-3.16	-0.84	-55.61				
Field Rank								
top 10%	0.00	0.00	0.00	0.00	136.78	0.000	68.38	0.000
11-25%	-0.44	-1.22	0.01	-5.41				
26-50%	-1.30	-0.31	0.14	-9.14				
51-75%	-1.50	-3.00	-0.08	-27.48				
bottom 25%	-2.72	-5.15	-0.37	-25.66				
Teach								
1 course	0.00	0.00	0.00	0.00	149.51	0.000	140.46	0.000
2 courses	-0.19	-3.82	-0.19	7.06				
3 courses	-1.47	-6.71	0.09	3.86				
4 courses	-2.81	-10.45	0.20	-4.95				
5 courses	-4.32	-19.49	-0.04	-58.27				
Gen. Sem./wk								
1	0.00	0.00	0.00	0.00	16.82	0.001	0.00	
2	-0.06	-0.06	-0.06	-0.06				
3	-0.50	-0.50	-0.50	-0.50				
4 or more	-0.20	-0.20	-0.20	-0.20				
Seminars in field								
none	0.00	0.00	0.00	0.00	71.94	0.000	66.34	0.000
occasional	1.04	-0.85	-0.24	-3.44				
1 per week	1.00	1.75	-0.41	1.32				
StatusQuo								
not home dept.	0.00	0.00	0.00	0.00	154.00	0.000	13.17	0.004
home dept.	1.94	1.49	1.55	-18.26				
Intercepts	0.00	-1.02	-0.40	-1.28	30.56	0.000		
CitesYr (covariate)	0.00	0.01	-0.04	0.01	11.64	0.009		

Table 3: one-Class Model Estimates

Attributes	**param.**	**Wald**	**p-value**	**importance**	**c.p. probability**
Salary				0.59	na
Salary<=86	0.08	83.70	0.000		
86<Salary<=107	0.05	60.97	0.000		
107<Salary<=140	0.04	88.43	0.000		
Salary>140	0.02	91.15	0.000		
Salary50%High				0.02	
No	0.00	11.11	0.001		0.60
Yes	-0.40				0.40
Dept. Rank				0.10	
1 to 5	0.00	271.38	0.000		0.27
6 to 10	-0.17				0.23
11 to 15	-0.64				0.14
16 to 20	-0.58				0.15
21 to 30	-1.11				0.09
31 to 40	-1.39				0.07
41 to 50	-1.65				0.05
Field Rank					
top 10%	0.00	156.54	0.000	0.07	0.31
11-25%	-0.23				0.25
26-50%	-0.44				0.20
51-75%	-0.73				0.15
bottom 25%	-1.23				0.09
Teach				0.14	
1 course	0.00	443.95	0.000		0.40
2 courses	-0.31				0.29
3 courses	-0.82				0.18
4 courses	-1.33				0.10
5 courses	-2.42				0.04
Gen. Sem./wk				0.02	
1	0.00	12.87	0.005		0.26
2	0.09				0.28
3	-0.19				0.21
4 or more	-0.05				0.25
Seminars in field				0.01	
none	0.00	10.23	0.006		0.31
occasional	0.04				0.32
1 per week	0.21				0.38
StatusQuo				0.05	
not home dept.	0.00	91.49	0.000		0.29
home dept.	0.87				0.71

Table 4: four-Class Model: importance of attributes

	Class1	Class2	Class3	Class4
Salary	0.61	0.65	0.35	0.42
Salary40%Low	0.00	0.03	0.16	0.05
Salary50%High	0.00	0.04	0.01	0.05
Dept. Rank	0.09	0.05	0.10	0.16
Field Rank	0.08	0.04	0.06	0.08
Teach	0.12	0.15	0.04	0.18
Gen. Sem./wk	0.01	0.00	0.06	0.00
Seminars in field	0.03	0.02	0.05	0.01
StatusQuo	0.05	0.01	0.18	0.05

Table 5: four-Class Model: c.p. Probabilities for Nominal Attributes

	Class1	Class2	Class3	Class4
Salary40%Low				
Yes	0.54	0.99	0.20	0.00
Salary50%High				
Yes	0.53	0.00	0.49	0.00
Dept. Rank				
1 to 5	0.36	0.26	0.23	0.03
6 to 10	0.32	0.04	0.21	0.00
11 to 15	0.15	0.00	0.10	0.97
16 to 20	0.08	0.68	0.12	0.00
21 to 30	0.05	0.00	0.10	0.00
31 to 40	0.02	0.00	0.14	0.00
41 to 50	0.01	0.01	0.10	0.00
Field Rank				
top 10%	0.45	0.48	0.21	1.00
11-25%	0.29	0.14	0.21	0.00
26-50%	0.12	0.35	0.24	0.00
51-75%	0.10	0.02	0.19	0.00
bottom 25%	0.03	0.00	0.14	0.00
Teach				
1 course	0.47	0.98	0.20	0.00
2 courses	0.39	0.02	0.16	0.96
3 courses	0.11	0.00	0.21	0.04
4 courses	0.03	0.00	0.24	0.00
5 courses	0.01	0.00	0.19	0.00
Gen. Sem./wk				
1	0.30	0.30	0.30	0.30
2	0.28	0.28	0.28	0.28
3	0.18	0.18	0.18	0.18
4 or more	0.24	0.24	0.24	0.24
Seminars in field				
none	0.15	0.14	0.41	0.21
occasional	0.43	0.06	0.32	0.01
1 per week	0.41	0.80	0.27	0.78
StatusQuo				
home dept.	0.87	0.82	0.83	0.00
CitesYr (covariate)				
1-20	0.13	0.12	0.22	0.13
21 - 35	0.14	0.13	0.14	0.14
36 - 62	0.15	0.12	0.20	0.09
63 - 92	0.16	0.17	0.09	0.17
93 - 123	0.13	0.20	0.06	0.21
.	0.30	0.27	0.31	0.26
Mean	16.14	18.36	11.37	17.40

Table 6: four-Class Model: c.p. Probability Means for Nominal Attributes

	Class1	Class2	Class3	Class4
Salary40%Low				
No	0.42	0.01	0.29	0.28
Yes	0.51	0.41	0.07	0.00
Salary50%High				
No	0.33	0.31	0.14	0.22
Yes	0.73	0.00	0.27	0.00
Dept. Rank				
1 to 5	0.62	0.20	0.16	0.02
6 to 10	0.76	0.05	0.19	0.00
11 to 15	0.31	0.00	0.08	0.61
16 to 20	0.19	0.70	0.11	0.00
21 to 30	0.56	0.00	0.43	0.00
31 to 40	0.31	0.01	0.68	0.00
41 to 50	0.22	0.08	0.69	0.00
Field Rank				
top 10%	0.43	0.20	0.08	0.29
11-25%	0.66	0.14	0.19	0.00
26-50%	0.33	0.41	0.26	0.00
51-75%	0.54	0.06	0.41	0.00
bottom 25%	0.34	0.01	0.65	0.00
Teach				
1 course	0.48	0.44	0.08	0.00
2 courses	0.51	0.01	0.08	0.39
3 courses	0.52	0.00	0.41	0.06
4 courses	0.23	0.00	0.77	0.00
5 courses	0.08	0.00	0.92	0.00
Gen. Sem./wk				
1	0.46	0.21	0.18	0.15
2	0.46	0.21	0.18	0.15
3	0.46	0.21	0.18	0.15
4 or more	0.46	0.21	0.18	0.15
Seminars in field				
none	0.35	0.14	0.37	0.15
occasional	0.73	0.04	0.22	0.00
1 per week	0.37	0.32	0.10	0.22
StatusQuo				
not home dept	0.21	0.14	0.12	0.53
home dept.	0.56	0.23	0.21	0.00
CitesYr (covariate)				
1-20	0.41	0.17	0.28	0.14
21 - 35	0.47	0.20	0.18	0.15
36 - 62	0.48	0.18	0.26	0.09
63 - 92	0.49	0.23	0.11	0.16
93 - 123	0.43	0.28	0.07	0.21
.	0.48	0.19	0.20	0.13