Do Economics Departments Search Optimally in Faculty Recruiting?*

by

Yongmin Chen and Terra McKinnish
yongmin.chen@Colorado.edu, mckinnis@Colorado.edu
303-492-8736, 303-492-6770
Department of Economics, UCB 256
University of Colorado at Boulder
Boulder, CO 80309-0256
FAX:303-492-8960

December 2003

* We thank two referees, Dan Black, Dan Hamermesh, Tom Holmes, Ron Smith, and colleagues at the University of Colorado at Boulder for helpful discussions. Excellent research assistance was provided by Thitima Puttitanun. Financial support from the National Science Foundation under grant #SES-9911229 and #SES-9819142 is gratefully acknowledged.

Do Economics Departments Search Optimally in Faculty Recruiting?

Abstract

Casual observation of faculty searches by economics departments indicates that some departments search primarily in a narrow subfield, while others search in several general or even all fields. In this paper we ask: What is the optimal search scope for a recruiting department? And second, do departments search optimally? We develop a simple search model in which optimal search scope is shown to increase in department quality. Using data from *Job Openings for Economists*, we find that higher-ranked departments do conduct broader searches. We correct for measurement error in department rankings by instrumenting a reputation-based ranking with a publication-based ranking. We find that a 10-place difference in department ranking is associated with 3.5-4.8 more JEL subfields listed in a position announcement.

JEL codes: J44, J64, D83, L8
Keywords: Employer Search, Search Scope, Faculty Recruiting, Economics Department Rankings

1. Introduction

When an economics department decides to recruit new faculty, it must decide in which fields to conduct the search. Casual observation suggests that the scope of recruiting searches varies widely, with some departments searching primarily in a narrow subfield and others searching in several general or even all fields. It is generally recognized that the very top departments tend to engage in very wide "best athlete" searches. Among departments that engage in narrower searches, on the other hand, it is not uncommon to hear complaints ex post that the search should have been broader. Is it therefore the case that these departments are making a sub-optimal choice to search narrowly? It would seem, however, that economic departments, more so than other departments, should be making economically rational decisions when choosing search scope.[1]

In this paper we develop a simple model of how economics departments can optimally choose search scope in faculty recruiting. We show that the optimal search scope is increasing in the quality rank of the department. We use postings in *Job Openings for Economists (JOE)* to estimate the relationship between department rank and search scope and find that higher-ranked departments engage in broader searches than lower-ranked departments. The relationship is robust to the exclusion of the top-ranked departments from the sample. Since there is some debate about how well various department rankings reflect true department quality, we instrument a reputation-based ranking with a publication-based ranking to correct for measurement error. We find that a 10-place difference in department ranking is associated with 3.3-4.6 more *Journal of Economic Literature (JEL)* subfields in a position announcement.

The rest of the paper is organized as follows. Section 2 presents our model, Section 3 discusses the data and presents our empirical analysis and Section 4 concludes.

---

[1] Previous research has shown that economists are more likely to exhibit behavior predicted by a rational economic model than non-economists (Maxwell and Ames, 1981).

2. The Model

We consider a simple model that focuses on a department's decision in choosing the number of fields to search and show that the optimal number of fields searched is increasing in department quality. Other work on employer search has noted the benefits to some employers of broadening the applicant pool. Much like our finding that departments with higher quality standards will search more broadly, Barron, Bishop and Dunkelberg (1985) show that employers will search over more candidates and/or more intensively if the education requirements for the position are high. Barron, Berger and Black (1997) argue that there is greater variation in productivity at higher levels of human capital; therefore it is optimal for employers searching for workers with more formal education to spend more on search. Lang (1991) shows that employers for whom a job vacancy is the most costly will offer a higher wage, therefore increasing the number of prospective applicants.

Because the need to decide ex ante the fields to advertise in *JOE* largely precludes the use of sequential search methods (e.g. Stigler, 1961; Morgan, 1983; Weitzman, 1979), our model is essentially a fixed-sample-size search problem. A key feature of our model is that each department has a quality cut-off that reflects the department's ranking. Higher ranked departments will have a higher quality cut-off. Applications below this cut-off are thrown out without cost, and applications above the cut-off are reviewed more extensively with some positive cost.[2] Therefore, if a high-ranked department with a high quality cut-off searches narrowly, it may not receive any applications above its cut-off. In addition, because the higher-ranked department can ignore most applications without cost, the cost involved in expanding the search to other fields is lower than those incurred by lower-ranked departments with lower cut-offs. These two effects will be

[2] Alternatively, we can think that when an applicant sees the ad of a department, he will not apply if his quality is below the department's cut-off. We, however, wish to avoid modeling strategic decisions of applicants.

important in explaining why a higher-ranked department is better off expanding its search to more fields.

To formalize the model, there are $i=1,...,M$ fields in which a department can conduct its search. Each field searched by the department produces one applicant, whose quality, q_i, is a random draw from a Uniform Distribution on support [0,1]. For each department there is an exogenous quality cut-off, k, where $k \in (0,1)$ and is increasing in the reputation or ranking of the department. The department will not accept any candidate for whom $q<k$. Each department knows, without cost, if $q_i<k$ and disposes of these applications, but does not know the actual value of q_i. The department reviews each application with $q_i \geq k$ at cost c to determine the true quality level. Intuitively, one can think of the department doing an initial "quick sort" of applications into two piles, one of which will be discarded and the other reviewed in more detail in order to determine how the applicants in that pile rank relative to each other. We assume that the department has perfect and costless information on the binary outcome of whether the applicant is above or below the quality cut-off, so that every application discarded is in fact below the cut-off and every application reviewed meets the cut-off.

After reviewing the applications above the cut-off, the department then makes an offer to the applicant with the highest quality. We assume that an applicant accepts an offer from a department of quality k with probability k, so the better the reputation of the department, the more likely an applicant will accept an offer from that department. For simplicity, we do not allow the department to make repeated or sequential offers, nor allow the department to make an offer to an applicant of lower quality in order to increase the probability of acceptance.

Without loss of generality, assume that a department, if it searches at all, searches fields

$i = 1,...,m$ where $1 \le m \le M$. Let Q_i be the quality of the applicant from field *i* and $Q_{\max}$ represent the highest quality application received by the department:

$$Q_{\max} = \max\{Q_i : i = 1,...,m\}\ , \tag{1}$$

where the probability distribution of each Q_i is:

$$F_Q(q) = q, \quad 0 \le q \le 1\ . \tag{2}$$

We will find it mathematically convenient to define a quality variable that is censored at the department's quality cut-off, k:

$$Q_c = \begin{cases} Q_{\max} & \text{if } Q_{\max} > k \\ k & otherwise \end{cases}\ . \tag{3}$$

It seems natural that a department's surplus from recruiting an applicant of quality *q*, conditional on the applicant accepting the offer, should be proportional to *q-k*. This term clearly needs to be standardized by quality rank; otherwise the returns to performing any search will be negligibly small for the very highest ranked departments. We thus assume this surplus to be

$$\frac{q_c - k}{1 - k}\ .$$

Notice that by our assumption, for any $k \in (0,1)$, the surplus equals 0 if the quality of the new hire is equal to the department's *k* and equal to1 if the quality of the new hire is 1. Notice, also, that this surplus is decreasing in *k*. Thus, for any given value of *q*, lower-ranked departments will receive the greater surplus.

Since the offer from a department of rank *k* is accepted with probability *k*, the department's search benefit is

$$v(k, q_c) = k\,\frac{q_c - k}{1 - k}\ .$$

Figure 1 illustrates how the benefit function varies with q and k for 2 values of k: .4 and .6. At low values of q, the benefit in both cases is zero. Between .4 and .6, only the lower-ranked department receives positive benefit. For values of q just above .6, the lower-ranked department still receives the larger benefit because the difference between q and k is so much greater. Because the slope of the function is steeper for higher-ranked departments, reflecting the fact that candidates are more likely to accept their offer, the high-ranked department receives the larger benefit at high values of q.[3]

The department's payoff from searching m fields is therefore

$$y(m, q_c) = k\frac{q_c - k}{1-k} - cn\ , \tag{4}$$

where n is the number of applications that are above the quality cut-off and are therefore actually reviewed by the department at cost c per person.[4] Obviously, $n \leq m$.

Then, the probability distribution of $Q_{\max}$ is

$$F_m(q) = q^m, \quad 0 \leq q \leq 1 \tag{5}$$

and the expected quality of the top applicant, given there is at least one applicant above the quality cut-off is:

$$E(Q_{\max} \mid Q_{\max} \geq k) = \int_k^1 q\left(\frac{mq^{m-1}}{1-k^m}\right)dq = \left(\frac{m}{m+1}\right)\left(\frac{1-k^{m+1}}{1-k^m}\right). \tag{6}$$

Therefore, the expected quality of the top applicant from the search of m fields is:

[3] Likewise, the result of Barron, Bishop and Dunkelberg (1985) requires that the higher the education requirements for the position, the greater the value of an increment in the applicant's ability. This greater return to an increase in applicant quality is a critical presumption to the finding in both models that employers with higher standards will search more broadly.

[4] Because the department does not know the actual quality of the applicant (beyond that it is at least k), it cannot choose to review applications based on more detailed information about the applicants' qualities.

$$
\begin{aligned}
E(Q_c) &= E(Q_{\max} \mid Q_{\max} \geq k)\Pr(Q_{\max} \geq k) + k\Pr(Q_{\max} < k) \\
&= \left(\frac{m}{m+1}\right)\left(\frac{1-k^{m+1}}{1-k^m}\right)(1-k^m) + k^{m+1} \\
&= \frac{m+k^{m+1}}{m+1}
\end{aligned}
$$

Thus the expected payoff for a department of rank k from searching m fields is

$$
\begin{aligned}
\tilde{y}(m) &= \left(\frac{k}{1-k}\right)(E(Q_c)-k) - cE(n) \\
&= \left(\frac{k}{1-k}\right)\left(\frac{m+k^{m+1}}{m+1} - k\right) - cm(1-k)
\end{aligned}
$$

A department's problem then becomes

$$
\max_{m \in \{0,\ldots,m\}} \tilde{y}(m),
$$

where for notational convenience we define $\tilde{y}(0) \equiv 0$. We have:

Lemma 1 *For a department of rank k, there exists a unique optimal scope of search, m*; and* $m^* \in [0, M]$ *satisfies*

$$
\Delta\tilde{y}(m^*-1) \geq 0 \quad \text{and} \quad \Delta\tilde{y}(m^*) < 0, \tag{8}
$$

where we define $\Delta\tilde{y}(-1) \equiv 0$*, and* $\Delta\tilde{y}(M) < 0$.[5]

Proof. See Appendix A.

Finally, we have:

Proposition 1 *The optimal scope of search, m*, (weakly) increases in k.*

Proof. See Appendix A.

It is therefore optimal for higher-ranked departments to search more broadly across economics fields than lower-ranked departments. A broader search is optimal for higher-ranked

[5] Notice that m^* changes as k changes and so does $\Delta\tilde{y}$, although for convenience we have suppressed the k in both expressions.

departments because of three factors. First, higher-ranked departments have higher quality standards. It is therefore likely that a narrow search may fail to produce an applicant of sufficient quality. Second, because a higher-ranked department will dispose of more applications without cost, the cost of expanding the search to more fields is lower than that experienced by lower-ranked departments. Third, while the surplus for hiring a candidate of any particular quality is higher for lower-ranked departments, the probability an applicant will accept an offer from the department is higher for higher-ranked departments. This prevents the search benefit to lower-ranked departments from universally dominating the search benefit to higher-ranked departments.

We note that the simple model we have presented abstracts away from some potentially important components of the search process. For instance, faculty members in a department may have different opinions about which field has the highest need for a new hire and which candidate has the highest quality. When several fields are listed for the search, the candidate to be hired may depend on both quality and field, reflecting coalitions within the department on what the department's needs are.[6] We avoid modeling the possible strategic behavior within the department by assuming that the department is able to reach a consensus on the measurement of the quality of candidate.

We also note that, because our simple model omits many features of what is actually a very complex process, it is easy to offer alternative explanations that would also generate a relationship between department quality and search scope. For example, higher-ranked departments could have better personal connections to other departments and greater expertise that allow them to evaluate the quality of applicants with lower costs. In addition, lower-ranked departments tend to exist in lower-ranked universities and these universities are sometimes less supportive of broad-based

[6] This process could be consistent with our model if the measurement of the highest quality candidate reflects such considerations and as long as the expected value of this highest quality increases in the number of the fields searched.

recruiting searches. Furthermore, higher-ranked departments are often larger and have a broader range of fields represented among their faculty. As a result, these departments can recruit over a broader range of fields and still find candidates that match with the interests of the current department faculty. We do not dispute that there might be differences in institutional structure, information or preferences between higher-ranked and lower-ranked departments that influence search behavior. Our model, however, shows that one can generate a relationship between search scope and department quality without assuming these sorts of inherent differences between departments. We further believe that the intuition behind the result of our model, that of the thinness of the market and free disposal of low-quality applications for high-quality departments, reflects key features of real-life search behavior on the part of economics faculty.[7]

There is one specific, alternative model that we deal with directly in our empirical analysis. Lower-ranked departments, particularly smaller departments, might find it advantageous to specialize in a few fields in order to build up a strong reputation in one or two specializations. These departments will tend to engage in narrower searches for reasons other than those implied by our model. Specifically, these departments will be considering match-quality, how well the candidates' research interests are aligned with those of the department, as well as absolute quality. In our empirical analysis, we create a measure of department concentration across fields based on publication output. We find that the relationship between department rank and breadth of search is robust to the inclusion of this control variable.

[7] For simplicity we have not considered the behavior of the labor market where matching and sorting between departments and applicants take place. Gan and Li (2002) focus on this issue and make the point that even holding the ratio of candidates to positions constant, a match will be more likely in thicker markets with more candidates and more positions. While in our model the department benefits from an expanded search due to the increase in the number of applications, Gan and Li's result suggests that there is an additional benefit of placing the department's search in a thicker market.

3. Empirical Analysis

There has been a small amount of empirical research done on the search behavior of employers. Barron, Bishop and Dunkelberg (1985) and Barron, Berger and Black (1997) confirm empirically that employers search more extensively (over more candidates) when the education requirements for the job are higher. There has been little formal analysis of search behavior of economists. Gan and Li (2002) use *JOE* listings from 1999-2000 to investigate the probability of a job vacancy filling in a “thicker” field versus a “thinner” field and find that job vacancies are more likely to be filled in fields with a larger number of positions and candidates, even if the ratio of candidates to positions is constant. In a less formal study, Carson and Navarro (1988) report the results of a survey of economics departments concerning their recruiting practices. Their results provide some preliminary support for our hypothesis in that they find that only 24% of top 20 departments report that a candidate’s fields of specialization are of great importance in the decision to schedule an interview compared to 61% of 380 other departments. In fact, 35% of top 20 departments reported that field was of slight or no importance compared to only 6% of the other economics departments.

The data used in our empirical analysis are collected from the October and November issues of *JOE* from 1997-2000. The October and November issues are used for two reasons. First, these two issues contain the vast majority of job announcements for tenure-track or tenured positions in research-oriented departments, which are the focus of our analysis. Second, *JOE* does not allow departments to list the same announcement two months in a row, so we can be sure that our data set does not contain duplicate observations for the same position opening. We limit our sample on several different dimensions. First, we only include position announcements from domestic economics departments. Announcements from foreign universities, policy schools, research institutes, private firms and government agencies are excluded. Second, we only include announcements from departments ranked in the 1993 National Research Council (NRC) or the 1998 *US News and World Report* economics department rankings. This limits our focus to the top 110 departments in the US. Third, only announcements for full-time tenure-track or tenured positions are included in the analysis. Fourth, announcements for special positions, such as department or endowed chairs, are excluded. Fifth, announcements from business schools for business school positions (such as finance) are excluded. Positions announced by economics departments that are located in business schools are, however, included in the data.

The purpose of these sample selection criteria are to exclude announcements that by their very nature are more likely to involve a narrower search. We exclude lower-ranked departments, because the fact that they tend to be teaching-oriented changes the interpretation of the field listings. For example, a research-oriented department might list several fields in their announcement indicating that they are willing to look at applicants with research interests in any of those fields. In contrast, a teaching-oriented department might list several fields to indicate that they need someone who can teach courses in all of those fields.

We obtain rankings of economics departments from four different sources. The 1993 National Research Council (NRC) rankings of 107 departments and the 1998 *US News and World Report* rankings of 62 departments are both based on surveys of economics faculty. These two reputation-based rankings have a Spearman's rank correlation coefficient of .96. We also consider two rankings based on journal publications. Scott and Mitias (1996) rank 240 departments based on total pages published per faculty member in a list of 36 journals for the years 1984-93. Dusansky and Vernon (1998) rank the top 50 departments based on pages published in the top 8 general-interest journals for the years 1990-94. We will conduct analysis with all four rankings, but our preferred ranking that we use in most analysis is the NRC ranking. Two advantages of this ranking are that it includes a large number of departments and is correlated at .9 or better with both the *US News* and Scott and Mitias rankings. In addition, a measure of reputation as perceived by other economics faculty is likely to be good indicator of the willingness of a faculty recruit to accept a job offer over offers from other departments. The Spearman's rank correlations between the Dusansky and Vernon ranking and the other three rankings range from .72 to .77. As such, it would be useful to use this alternative ranking as a robustness check. Unfortunately, with only 50 departments included in the ranking, its use substantially limits our sample size.

For our initial analysis, we consider whether or not a department conducts a broad "Any Field" (AF) search. In the first two columns of Table 1, we report, for each year, the average NRC ranking of those departments that do not list AF in any of their position announcements that year and those departments that do list AF in at least one position announcement. The average ranking of departments not conducting an AF search ranges from 52.2 to 57.7.[8] In contrast, the average ranking of departments conducting an AF search ranges from 26.3 to 31.4. The differences in these means are statistically significant at the .01 level in all four years.

Further inspection of the AF postings allows them to be divided into two groups. Some departments list AF in their *JOE* ad, but place additional restrictions on the position elsewhere in the posting. For instance, in the November 1997 issue of *JOE*, Southern Methodist University advertises a search and lists AF as the only field, but the text of the ad states "Although the Department's primary interest is in the areas of international economics and international economic development, the outstanding candidates in other fields will also be considered.'" Any listing that qualifies the AF search either by listing additional fields or by adding additional restrictions in the

[8] The *US News* rankings of Emory, CMU and UC-Irvine were used since they did not receive NRC rankings. Recall that the correlation between these two rankings is .96.

text of the ad are designated as "AF Qualified" searches. Those that do not are designated as "AF Unqualified" searches.

We compare the average NRC rankings of these two groups in the columns 4 and 5 of Table 1. It is striking that the average rankings of those departments who qualify their AF search are relatively close to the average rankings of the departments who do not conduct an AF search at all. The average NRC ranking of the AF qualified group ranges from 44.9 to 51.1. In comparison, the average ranking of departments who do not qualify their AF search ranges from 13.6 to 25.9. The difference in the means between these two groups is significant at the .01 level in three of the four years. Therefore, this analysis indicates that higher-ranked departments are more likely to conduct broad AF searches, and in particular, higher-ranked departments are more likely to list AF as their search code without further clarification.

For our regression analysis, the unit of observation is a position announcement. Many departments post multiple announcements because they are recruiting for more than one position. Our regression analysis is appropriately weighted to account for the fact that departments advertising more positions have more observations in the data. If a position announcement advertises multiple positions and it is clear which of the listed fields are intended for which positions, the position announcement is separated out into multiple observations. Because some announcements cannot be decomposed this way, we control for the number of positions advertised in the announcement in some of our analysis below.

In order to more fully use the information in the announcement, we construct a measure of search scope based on all of the fields listed in the posting. In the JEL classification system, there are 19 general headings (such as D0-Microeconomics), each of which contains one to nine subheadings (such as D4-Market Structure and Pricing), for a total of 100 subheadings. We take as our measure of search scope the fraction of those 100 subheadings that are included in the announcement.[9] For example, a November 1997 position announcement by the University of Hawaii lists C1-Econometrics, J0-Labor Economics and FO-International Trade\&Finance as fields. C1 counts as one subheading, J0 contains seven subheadings and F0 contains four subheadings. Therefore, this announcement would cover 12 subheadings, for a search scope value of .12. Any position announcement listing AF receives a search scope value of 1.0.

There are some obvious limitations to our search scope measure. The University of Hawaii example above was chosen specifically to illustrate this limitation. First of all, the announcement lists C1-Econometrics, which only adds .01 to the search size even though econometrics is a large field. Some announcements list C0-Econometrics as opposed to C1, which would generate a larger search scope value. In addition, while the ad lists C1, J0 and F0 as *JEL* codes, the text of the ad indicates that the department wants an econometrician who has labor or international as a secondary field. In this case, the scope of the search is somewhat narrower than the *JEL* listings imply. Despite this limitation, we are reluctant to introduce a substantial subjective component into our analysis by trying to incorporate the additional information provided in the text of the ads.

It is also the case that the final outcome of a search might be very different from what was indicated in the department's ad. We do not have data on the final outcome of the search, so we assume that the ad placed by the department is an indicator of that department's true intent.[10] We

---

[9] Our search scope measure essentially weights each general field by the number of subfields listed in the *JEL* classifications. An announcement for a small general field (such as KO-Law and Economics or IO-Health, Education and Welfare, whichhave 4 and 3 subfield, respectively) will therefore have a narrower search scope measure than a position announcement for a large general field (such as CO-Mathematical and Quantitative Methods or DO-Microeconomics, each of which has 9 subfields). We experimented with an alternative weighting scheme in which each general field was weighted by the fraction of 1999 *JOE* announcements listing that field. The correlation between the search scope measure obtained using these weights and our original search scope measure was .99, so we restricted our analysis to the original measure.

[10] In many cases, due to equal employment/affirmative action rules, it is difficult for a department to hire in fields outside those listed in its JOE ad.

only need to assume that departments that intend broader searchers typically place ads that generate larger search scope values.

In Figure 2, we plot our search scope variable against the department's NRC ranking for the 531 observations in our data set. Figure 2 shows that most department searches are fairly narrow. The median search, among non-AF searches, has a search scope value of .09 (the size of a larger general field). The 25th percentile is .04 (the size of a small general field), and the 75th percentile is .18. There is a clear negative correlation between search scope and NRC rank. As was suggested by Table 1, the AF searches are clustered at the higher ranks. What Figure 2 reveals, however, is that even ignoring the AF searches, there still appears to be a negative relationship between search scope and department rank.

In the first column of Table 2, we report the pair-wise correlation coefficients between field size and the four different department rankings. In the second column, we report the correlation coefficients obtained when the AF searches are excluded from the data. For the full sample results in the first column, the correlations range between -.31 and -.40, all of which are statistically significant at the .01 level. For the results when AF searches are excluded, three of the four correlation coefficients are between -.25 and -.3 and are statistically significant at the .01 level.

Given the rather large discontinuity in the search size variable displayed in Fig 2, OLS regression analysis of search scope is inappropriate. Departments generally do not list 80 or 90 percent of the economics fields in a position announcement, so values of .8 and .9 are not observed for the search scope variable. It seems reasonable that if a department were open to applications in the majority of economics fields, they would simply advertise an AF search. We therefore estimate a tobit model for our multivariate analysis. The largest value of search scope for a non-AF search we observe in our sample that is .73. We therefore take this value as our censoring point.

In Table 3, we report sample means for all variables used in our Tobit analysis. We report both unweighted and weighted means. The weights are designed to equalize weight across economics departments, adjusting for the fact that departments place different numbers of ads and therefore have different numbers of observations in the data. These weights are used in all our multivariate analysis.

In Table 4, we report the results of our Tobit analysis. The dependent variable is search scope. Control variables include indicator variables for whether or not the department is located in a business school or in a private university, indicator variables for whether the position is advertised as joint with another department, a junior-level search, a senior-level search (omitted category is open-rank search), a measure of department size and year effects.[11]

One control variable, publication concentration, requires some additional explanation. This variable is intended to proxy for the extent to which a department specializes in a subset of fields. The variable is calculated using all publications listed on *EconLit* in the year 2000. For each department, for each of the 19 general *JEL* fields, we calculate the number of articles published in 2000 that list that field as a *JEL* code in the *EconLit* abstract. Let $X_1, \ldots, X_{19}$ be the measures of total publications for each of the 19 fields and let $T = \sum X_i$ be the total number of publications from that department in 2000. Then the publication concentration measure is:

$$PublicationConcentration = \sum_{i=1}^{19} \left(\frac{X_i}{T} - \frac{1}{19} \right)^2$$

As would be expected, this measure is positively correlated with department rank (better departments are less concentrated), negatively correlated with size (larger departments are less

[11] The department size variable was obtained by counting full-time tenured or tenure-track faculty for the 2000-2001 academic year using department web pages.

concentrated), and negatively correlated with the search scope measure (more concentrated departments have narrower searches).

The first column of Table 4 reports the results of our baseline Tobit analysis. There is a statistically significant negative coefficient of -.0036 for NRC Rank, indicating that high-ranked departments tend to have broader searches. In addition, announcements from departments in business schools and announcements for joint positions tend to be narrower in scope. Larger departments tend to have broader searches. The only counter-intuitive sign is that for the logarithm of the publication concentration measure. It is positive, indicating that more concentrated departments have broader searches. This coefficient is very imprecisely measured and would better be interpreted as a finding of no relationship independent of department size and rank.[12]

One variable that is not included in the analysis in the first column is the number of positions advertised in the job announcement. An announcement that is intended to fill multiple positions will most likely list more fields than one that is intended to fill a single position. The number of positions is therefore an important control variable. Recall, however, that if a department is hiring for multiple positions, but separately lists the fields associated with each position, either in separate announcements or in the text of a single announcement, each position appears in the data as a separate observation. It is only if a department advertises multiple positions in a single job announcement without assigning specific fields to each position that the fields for multiple positions will be included in a single observation. A department that advertises three positions and only indicates that all three positions will be filled from a broad set of fields is arguably engaging in a much broader search than a department that advertises three separate narrow searches. Therefore, controlling for the number of positions advertised in an announcement in part

[12] A simple regression of search scope on the logarithm of publication concentration produces a statistically significant negative coefficient. The publication concentration measure becomes insignificant, although remains negative, as soon as department size is added to the model.

controls for one dimension on which departments can broaden their search. As a result, we report results with and without this control variable.

The results with the positions variable included are reported in the second column of Table 4. This variable is coded to equal one if only one position will be filled for that announcement, two if two positions are available and three if more than two positions are available.[13] As expected, the positions variable is positive and significant, indicating that announcements intended to fill multiple vacancies advertise in more fields than those intended to fill a single vacancy. The magnitude of the effect of department rank is diminished from -.0036 to -.0029.

The results in Table 4 could largely reflect the behavior of the top few departments. It is well known that a number of the top departments, such as Harvard, Yale and University of Chicago, tend to conduct "best-athlete" searches every year by advertising AF searches. We therefore repeat the analysis from Table 4 in Table 5, but using only those departments that do not appear in the top 10 of any of our four rankings. This eliminates 16 departments from the data and reduces our sample size from 531 to 430. The results in Table 5 indicate that the magnitude of the effect of department rank has been diminished, but the coefficient is still negative and statistically significant. The coefficient estimate is -.0025 when we do not control for the number of positions in the ad and is -.0019 when we do control for number of positions. The only other variables that remain significant in the regression are whether or not the position advertised is joint with another department and the number of positions advertised in the announcement.

[13] The coding of the positions variable required some subjective judgments. We found that while ads frequently indicated that one, two or three positions were available, it was extremely rare for more a number higher than three to be specified. On the other hand, terms such as "one or more positions," "two or more positions," and simply "positions" or "openings" were very common. We coded "one or more positions" as two positions. Listings specifying "two or more positions," "positions" or "openings" were coded as three or more positions. The very few advertisements that specified a number of positions greater than three were coded as three or more positions. It was our judgement that this coding best captured the intent of the ads.

The magnitude of the effect of rank on search scope is of modest, but very reasonable, magnitude. The coefficient estimates in Tables 4 and 5 indicate that a 10-place increase in department ranking is associated with 1.9 to 3.6 more subfields listed in a position search. It takes a difference in rank of 30 places to generate a difference in search scope equivalent to one of the major general fields (containing 6 to 9 subfields).

There is considerable debate over the extent to which department rankings reflect true department quality. In other words, quality rank is measured with error. If this is the case, then the coefficient estimate for quality ranking is attenuated towards zero and we underestimate the impact of quality ranking on search scope. One correction for measurement error would be to instrument the NRC ranking with a second measure of quality. If the measurement errors in the two quality measures are uncorrelated, this produces a consistent coefficient estimate. Of our three other rankings, we argue that the Scott and Mitias ranking is best-suited for this exercise. The *US News* ranking is, like the NRC ranking, a reputation-based ranking. Therefore, the measurement errors are likely to be correlated. The Dusansky and Vernon only includes fifty departments, substantially reducing our sample size. The Scott and Mitias ranking is publication-based, ranking departments by total pages in 36 journals from 1984-93 per faculty member, and available for all departments in the NRC ranking. The measurement error in the NRC ranking is most likely going to reflect the lag with which reputations adjust for departments that have improved or declined. In contrast, the measurement error in the Scott and Mitias ranking is more likely going to reflect factors such as high-quantity output in low-quality journals that contribute relatively little to reputation. Therefore, it seems likely that the two measurement errors are uncorrelated.

Instrumental variables (IV) estimation in linear models is very straightforward. In nonlinear models, however, IV estimation of errors-in-variables models fails to produce consistent coefficient estimates. Amemiya (1985) points out that econometric theory developed for nonlinear models with endogenous regressors is not applicable for nonlinear errors-in-variables models. Hausman, Newey and Powell (1995) implement IV estimation in the case of nonlinear errors-in-variables models with an additive error term, which does not apply to the case of the Tobit model. Carroll, Ruppert and Stefanski (1995) suggest that a useful approximation is obtained by estimating a generalized linear model in which the appropriate regressor is replaced with the predicted value from a first-stage regression on the alternative measurement.[14] Stefanski and Buzas (1995) show in a simulation study that this method substantially reduces bias due to measurement error in the case of logistic regression.

In Table 6, we therefore report Tobit results in which the NRC ranking is replaced with the predicted value from a first-stage regression on the Scott and Mitias ranking and the other control variables. While we do not claim that these estimates are consistent, we do claim that they are subject to less measurement error bias than those reported in Tables 4 and 5. The first column of Table 6 repeats the coefficient on NRC ranking from the Tobit regressions estimated in Tables 4 and 5. The second column reports the IV estimate. Instrumenting with the Scott and Mitias ranking increases the magnitude of the coefficient on NRC by a little over 30% in the full sample and by over 75% in the non-top10 sample. The NRC coefficients now range from -.0035 to -.0048. This suggests that a 10-place increase in department ranking is associated with 3.5 to 4.8 more subfields listed in a position search. A difference in ranking of 20 places generates a difference in search scope equivalent to a major general field (6 to 9 subfields).

We suspect that the inconsistency of our IV estimates due to the nonlinearity of the Tobit model is relatively small. We are able to almost exactly replicate the coefficients in Table 6 by

[14] We also try a slight modification to this approximation that is also suggested by Carroll, Ruppert and Stefanski (1995), but it had a negligible impact on the results.

setting the search scope measure to .8 for all AF searches and estimating OLS and linear IV regression models, suggesting that the nonlinearities in our model are relatively inconsequential.[15]

Additional IV analysis, not reported in the tables, shows that this relationship is much stronger for public universities than private universities. For private universities, a 10-place increase in department ranking is associated with 2.8 to 3.9 more subfields listed in a position search, while for public universities the equivalent response is 4.0 to 5.4 more subfields listed in a position search. This means that for public universities, a difference in rankings of only 15 places is enough to generate a difference in search scope equivalent to a major general field.

4. Conclusions

Our findings suggest that differences in search behavior across departments, with some departments engaging in very narrow searches and others engaging in very broad searches, are actually systematic differences that reflect economically rational behavior.

We would expect to see similar patterns in search behavior in other markets. For example, a moderately successful law firm might primarily recruit new employees from law firms in the local area, while a prestigious law firm with high quality standards is more likely to send out recruiters to campuses across the nation. In both cases, the search strategy is similar to that of the economics departments. The recruiters receive resumes from interested candidates and quickly selects (with little cost) those that exceed the firm's minimum quality threshold for (more costly) interviewing. The more prestigious law firm will recruit at more campuses across a broader geographic area in order to insure that they find enough prospective employees that exceed their higher quality threshold.

[15] Specifically, the coefficients from the OLS version of the first column of Table 6 are -.0033, -.0027, -.0025 and -.0021. The coefficients from the linear IV regression version of the second column of Table 5 are -.0045, -.0037, -.0043, and -.0035. A quick examination of Table 6 shows that these coefficients deviate no more than .0003 from the Tobit results.

References

Amemiya, Yasuo. 1985. "Instrumental Variable Estimator for the Nonlinear Errors-in-Variables Model." *Journal of Econometrics* 28: 273-89.

Barron, John, John Bishop and William Dunkelberg. 1985. "Employer Search: The Interviewing and Hiring of New Employees." *Review of Economics and Statistics* 67:43-52.

Barron, John, Mark Berger and Dan Black. 1997. "Employer Search, Training and Vacancy Duration." *Economic Inquiry* 35:167-92.

Carroll, R.J., D. Ruppert and L.A. Stefanski. 1995. *Measurement Error in Nonlinear Model*s. London: Chapman&Hall.

Carson, Richard and Peter Navarro. 1988. "A Seller's (& Buyer's) Guide to the Job Market for Beginning Academic Economists." *Journal of Economic Perspectives* 2(2):137-48.

Dusansky, Richard and Clayton Vernon. 1998. "Rankings of U.S. Economics Departments." *Journal of Economic Perspectives* 12(1):157-70.

Gan, Li and Qi Li, 2002. "Efficiency of Thin and Thick Markets." Working Paper, University of Texas-Austin.

Hausman, J.A., W.K. Newey and J.L. Powell. 1995. "Nonlinear Errors-in-variables: Estimation of some Engel Curves." *Journal of Econometrics* 65:205-33.

Lang, Kevin. 1991. "Persistent Wage Dispersion and Involuntary Unemployment." *Quarterly Journal of Economics* 181-202.

Maxwell, Gerald and Ruth Ames. 1981. "Economists Free-Ride, Does Anyone Else?" *Journal of Public Economics* 15:295-310.

Morgan, Peter. 1983. "Search and Optimal Sample Size." *Review of Economic Studies* 659-675.

Nationonal Research Council. 1993. *Research-Doctorate Programs in the United States: Continuity and Change,* eds. Marvin, Brendan Maher and Pamela Flatau. National Academy Press: Washington, D.C.

Scott, Loren and Peter Mitias. 1996. "Trends in Rankings of Economics Departments in the U.S.: An Update." *Economic Inquiry*.

Stefanski, L.A. and J.S. Buzas. 1995. "Instrumental Variables Estimation in Binary Regression Measurement Error Models." *Journal of the American Statistical Association*. 90:541-50.

Stigler, George. 1961. "The Economics of Information." *Journal of Political Economy* 213-225.

U.S. News and World Report. 1998. “Best Graduate Schools.”

Weitzman, Martin. 1979. “Optimal Search for the Best Alternative." *Econometrica* 641-654.

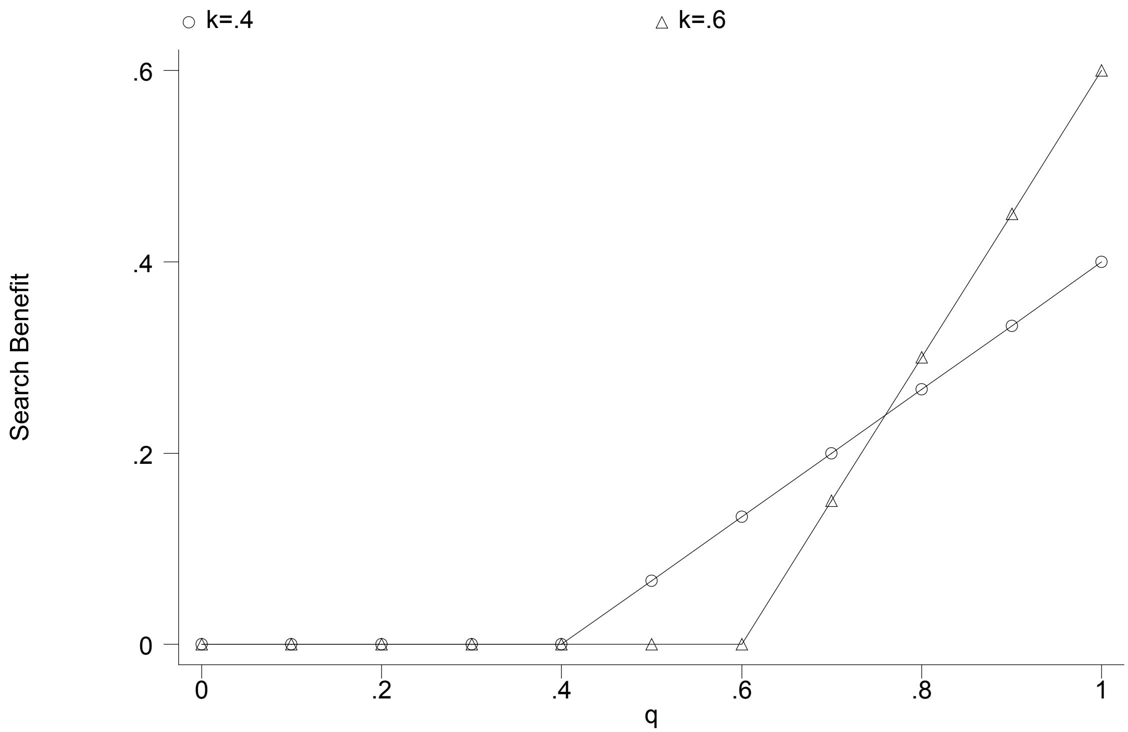

Figure 1. Search Benefit (*v*) as a function of Q

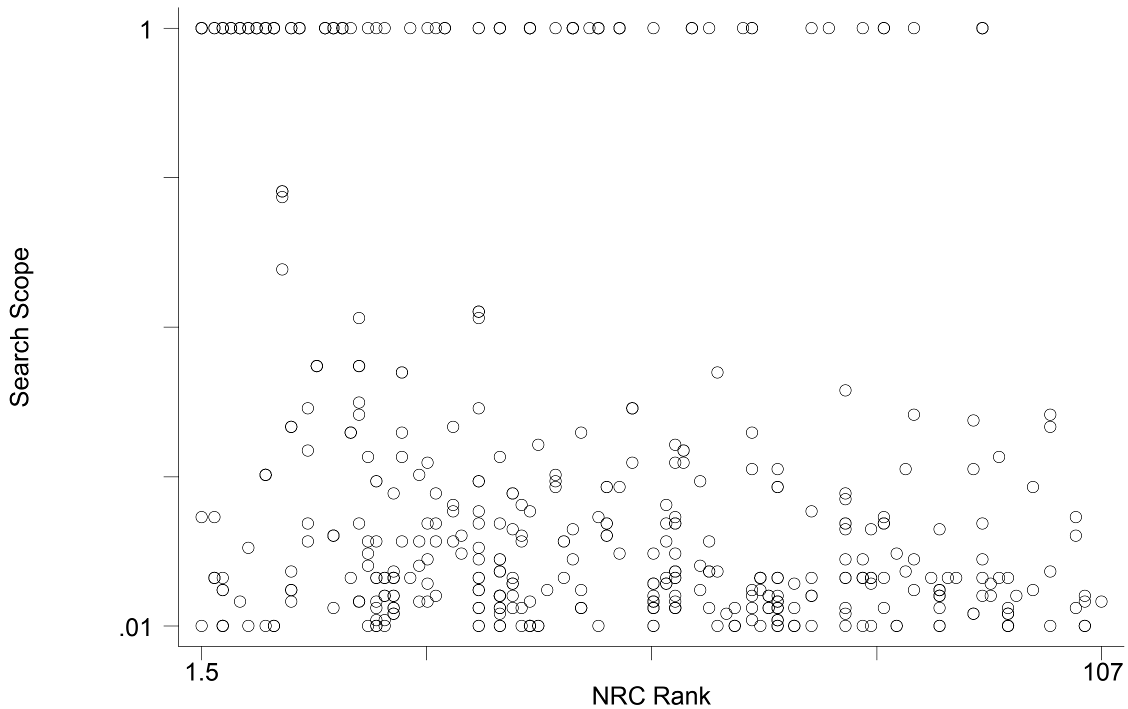

Figure 2. NRC Rank vs Search Scope

Table 1: Average NRC Ranking by Type of Search

Year	No AF Search	AF Search	T-Test	AF Qualified	AF Unqualified	T-Test
1997	57.65	26.33	0.000	44.86	13.59	0.000
	(3.70)	(4.07)		(5.41)	(2.92)	
	[55]	[27]		[11]	[16]	
1998	52.31	28.02	0.000	47.13	18.47	0.008
	(3.66)	(5.32)		(8.87)	(5.34)	
	[57]	[24]		[8]	[16]	
1999	55.29	29.64	0.000	51.14	21.28	0.006
	(3.80)	(5.12)		(12.04)	(4.09)	
	[52]	[25]		[7]	[18]	
2000	56.43	31.35	0.000	46.93	25.90	0.084
	(3.75)	(5.33)		(8.62)	(6.18)	
	[48]	[27]		[7]	[20]	

Notes: First two columns report the mean NRC rank of departments not advertising an Any Field search and those advertising at least one Any Field Search. Column 3 reports the p-value from t-tests for the first two columns. Column 4 reports mean NRC rank of departments advertising an Any Field search that is limited by additional field listings or additional clarification in the text of the announcement and column 5 reports mean NRC rank for those advertising an Any Field search with no additional limitations or qualifications. Column 6 reports p-values from t-tests of columns 4 and 5. Standard errors reported in parentheses. Sample sizes reported in brackets.

Table 2: Correlations Between Search Scope and NRC Ranking

Ranking	Full Sample	Search Scope <1
NRC	-0.398**	-0.294**
	[531]	[399]
US News	-0.330**	-0.254**
	[375]	[358]
Scott and Mitias	-0.387**	-0.295**
	[526]	[394]
Dusansky and Vernon	-0.314**	-0.089
	[293]	[197]

Notes: Table reports the correlation between department ranking and search scope variable for each of the four rankings. Sample size reported in brackets. **p-value<.01 *p-value<.05

Table 3: Sample Means

	Unweighted	Weighted
Search Scope	0.3468 (0.3922)	0.3458 (0.3858)
Search Scope<1	0.1308 (0.1287)	0.1386 (0.1310)
Business School	0.0923 (0.2897)	0.0758 (0.2649)
Private University	0.3992 (0.4902)	0.3564 (0.4794)
Joint Position	0.0546 (0.2274)	0.0474 (0.2126)
Junior Search	0.5235 (0.4999)	0.5807 (0.4939)
Senior Search	0.1789 (0.3836)	0.1269 (0.3332)
Department Size	28.38 (11.72)	25.82 (10.83)
Publication Concentration	0.0025 (0.0016)	0.0029 (0.0020)
# Positions in Ad	1.518 (0.7430)	1.481 (0.7165)
N	531	531

Notes: Table reports sample means of variables used in Tobit analysis. Standard deviations are reported in parentheses. Second column adjusts for the differential number of ads placed by different departments by re-weighting to equalize weight across economics department.

Table 4: Tobit Analysis of Determinates of Search Scope

	Without Positions Control	With Positions Control
NRC Ranking	-0.0036**	-0.0029**
	(0.0007)	(0.0007)
Business School	-0.2170**	-0.1689**
	(0.0549)	(0.0538)
Private University	0.0336	0.0253
	(0.0318)	(0.0308)
Joint Position	-0.2429**	-0.1985**
	(0.0646)	(0.0630)
Junior Search	-0.0460	-0.0010
	(0.0326)	(0.0326)
Senior Search	-0.0657	-0.0034
	(0.0487)	(0.0485)
Department Size	0.0066**	0.0053**
	(0.0019)	(0.0019)
Log(Publication Concentration)	0.0318	0.0344
	(0.0310)	(0.0300)
1998	-0.0782*	-0.0676
	(0.0392)	(0.0380)
1999	-0.0650	-0.0673
	(0.0396)	(0.0384)
2000	-0.0506	-0.0717
	(0.0402)	(0.0391)
# Positions in Ad		0.1212**
		(0.0218)
N	531	531

Notes: Table reports results from Tobit analysis. Dependent variable is search scope and censoring point is 0.731. Standard errors are reported in parentheses. **p-value<.01 *p-value<.05

Table 5: Tobit Analysis of Determinates of Search Scope Among Non-Top10 Departments

	Without Positions Control	With Positions Control
NRC Ranking	-0.0025**	-0.0019**
	(0.0007)	(0.0007)
Business School	-0.0670	-0.0428
	(0.0642)	(0.0626)
Private University	0.0072	-0.0043
	(0.0319)	(0.0311)
Joint Position	-0.1647**	-0.1326*
	(0.0634)	(0.0619)
Junior Search	-0.0022	0.0317
	(0.0332)	(0.0330)
Senior Search	-0.0074	0.0374
	(0.0511)	(0.0505)
Department Size	0.0028	0.0013
	(0.0021)	(0.0021)
Log(Publication Concentration)	0.0335 (0.0293)	0.0327 (0.0285)
1998	-0.0494	-0.0427
	(0.0390)	(0.0380)
1999	-0.0522	-0.0576
	(0.0392)	(0.0381)
2000	-0.0401	-0.0615
	(0.0397)	(0.0388)
# Positions in Ad		0.1068**
		(0.0217)
N	430	430

Notes: Table reports results from Tobit analysis. Dependent variable is search scope and censoring point is 0.731. Departments ranked in the top 10 of the NRC, US News, Dusansky and Vernon or Scott and Mitias rankings are excluded from the sample. Standard errors are reported in parentheses. **p-value<.01 *p-value<.05

Table 6: Coefficient on NRC Ranking in Baseline and IV Versions of Tobit

	Tobit	Tobit-IV
Full Sample	-0.0036**	-0.0048**
	(0.0007)	(0.0009)
Full Sample	-0.0029**	-0.0038**
Control for #Positions	(0.0007)	(0.0009)
Non-Top10 Departments	-0.0025**	-0.0044**
	(0.0007)	(0.0009)
Non-Top10 Departments	-0.0019**	-0.0035**
Control for #Positions	(0.0007)	(0.0009)

Notes: Table reports coefficient on NRC ranking from Tobit analysis of search scope, using .731 as the censoring point. Second column reports the coefficient on value of NRC ranking predicted from a first-stage regression on the Scott and Mitias ranking and control variables. Standard errors are reported in parentheses. **p-value<.01 *p-value<.05

Appendix A

We use the following result in both proofs:

Define $\Delta\tilde{y}(m)=\tilde{y}(m+1)-\tilde{y}(m)$ *for m. Then for any given k and* $0\leq m\leq M-1$*,*

$$\tilde{y}(m)=\left(\frac{k}{1-k}\right)\int_k^1 x^m(1-x)dx-c(1-k)$$

Proof. For $m\in(0,M-1]$,

$$\begin{aligned}\Delta\tilde{y}(m)&=\tilde{y}(m+1)-\tilde{y}(m)\\&=\left(\frac{k}{k-1}\right)\left(\frac{(m+1)+k^{m+2}}{m+2}-k\right)-c(m+1)(1-k)\\&\quad-\left(\left(\frac{k}{k-1}\right)\left(\frac{m+k^{m+1}}{m+1}-k\right)-cm(1-k)\right)\\&=\left(\frac{k}{k-1}\right)\left(\frac{1-k^{m+1}}{m+1}-\frac{1-k^{m+2}}{m+2}\right)-c(1-k)\\&=\left(\frac{k}{k-1}\right)\left(\int_k^1 x^m dx-\int_k^1 x^{m+1}dx\right)-c(1-k)\\&=\left(\frac{k}{k-1}\right)\int_k^1 x^m(1-x)dx-c(1-k).\end{aligned}$$

For $m=0$,

$$\begin{aligned}\Delta\tilde{y}(m)=\tilde{y}(1)-\tilde{y}(0)&=\left(\frac{k}{1-k}\right)\left(\frac{1+k^2}{2}-k\right)-c(1-k)\\&=\left(\frac{k}{1-k}\right)\int_k^1 x^0(1-x)dx-c(1-k)\end{aligned}$$

■

Proof of Lemma 1. Since

$$\begin{aligned}\Delta^2\tilde{y}(m)&=\Delta\tilde{y}(m+1)-\Delta\tilde{y}(m)\\&=\left(\frac{k}{1-k}\right)\int_k^1(1-x)x^m(x-1)dx\ =\\&=-\left(\frac{k}{1-k}\right)\int_k^1(1-x)^2x^m dx<0,\end{aligned}$$

$\Delta\tilde{y}(m)$ is a strictly decreasing function of *m* for $m \in [0, M-1]$. Therefore if $\Delta\tilde{y}(0) < 0$, $m^* = 0$; otherwise $m^* \geq 1$ and it is optimal to increase *m* until $\Delta\tilde{y}(m) = \tilde{y}(m+1) - \tilde{y}(m)$ just becomes negative. Therefore the optimal m^* must exist uniquely on [0,*M*] and satisfy $\Delta\tilde{y}(m^*-1) \geq 0$ and $\Delta\tilde{y}(m^*) < 0$.■

Proof of Proposition 1. It suffices to show that at any m^* associated with any given *k*, an increase in k increases $\Delta\tilde{y}(m)$. Notice first that:

$$\begin{aligned}
\frac{\partial \Delta\tilde{y}(m)}{\partial k} &= \frac{1}{(1-k)^2}\int_k^1 x^m(1-x)dx - \frac{k}{1-k}k^m(1-k) + c \\
&= \frac{1}{(1-k)^2}\int_k^1 x^m(1-x)dx - k^{m+1} + c \\
&> \frac{1}{(1-k)^2}k^m\int_k^1 (1-x)dx - k^{m+1} + c \\
&= \frac{k^m}{(1-k)^2}\frac{(1-k)^2}{2} - k^{m+1} + c \\
&= k^m(\tfrac{1}{2} - k) + c
\end{aligned}$$

Therefore, if $k \in (0, \frac{1}{2}]$, then $\dfrac{\partial \Delta\tilde{y}(m)}{\partial k} > 0$ for all *m*. If $k \in (\frac{1}{2}, 1)$, notice that since $\Delta\tilde{y}(m^*) < 0$ by construction, we have:

$$\left(\frac{k}{1-k}\right)\int_k^1 x^{m^*}(1-x)dx - c(1-k) < 0,$$

and hence

$$k^{m^*}\int_k^1 (1-x)dx < \int_k^1 x^{m^*}(1-x)dx < \frac{c}{k}(1-k)^2,$$

Therefore

$$\frac{k^{m^*}}{2}(1-k)^2 < \frac{c}{k}(1-k)^2.$$

Which implies that

$$m^* > \frac{\log(2c) - \log(k)}{\log(k)}.$$

It follows that, for any $k \in (\frac{1}{2}, 1)$,

$$m^* > \frac{\log(2c) - \log(2k-1)}{\log(k)}$$

But since for any $k \in (\frac{1}{2}, 1)$,

$$k^m(\tfrac{1}{2} - k) + c > 0 \Leftrightarrow m > \frac{\log(2c) - \log(2k-1)}{\log(k)}$$

we must have $\dfrac{\partial \Delta\tilde{y}(m)}{\partial k} > 0$ at *m*=*m** for any $k \in (\frac{1}{2}, 1)$. Thus at any m^* associated with any given $k \in (0,1)$, $\Delta\tilde{y}(m)$ increases in *k*. ■