# *Ability and Specialization among Economic Researchers*

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It is not obvious whether a firm's more talented workers should be more specialized, and in fact, the relationship between ability and specialization seems to differ across industries. In this paper, I examine the case of knowledge production in economic research, and find that abler economists tend to publish more general research. This result suggests substitutability between general and specialized skill in research.

JEL Classifications: D2, J2

## I. Introduction

Corporate managers with higher general human capital usually manage firms with greater spans of control;[1] on the other hand, better-qualified physicians and chefs generally specialize to a high degree. These examples suggest differences in the production function for different worker outputs. In this paper, I consider the relationship between general ability and specialization among a cohort of young economic researchers.

It is often claimed that general and specialized knowledge are substitutable to some degree in economic research. An economist or econometrician well trained in statistics or mathematics may contribute to knowledge on an issue by applying this general understanding to the specifics of the issue[2]. If general and specialized knowledge are substitutable in economic research, then higher ability researchers may generalize more relative to lower ability researchers. To test this hypothesis, I collected data on the publication records of young academic economists at 50 well-known economics departments. The results suggest that the economists with the greatest levels of general human capital do indeed specialize less.

These empirical results suggest several lessons for the economics of knowledge production. First, talented researchers and innovators will tend to make their mark in a wide variety of fields. Illustrative examples include Thomas Edison, Benjamin Franklin, and more recently Richard Feynman or Dean Kamen[3]. Moreover, a complaint commonly heard is that intellectuals who gain fame in one area of research are too often allowed to opine upon other

[1] See Gulamhusein (2005).
[2] For instance, note Becker (1976): "…I believe that what most distinguishes economics as a discipline from other disciplines in the social sciences is not its subject matter but its approach….I contend that the economic approach is uniquely powerful because it can integrate a wide range of human behavior," and the famous quip variously attributed: "Economics is what economists do."
[3] American inventor, holding over 150 patents, including those for the wearable insulin pump, the stair-climbing wheelchair, and the Segway personal transportation system.

areas of research.[4] However, the results here suggest that, at least to some degree, abler intellectuals optimally *should* engage in broader research interests. On a similar note, the long-term intellectual trend in the economics profession towards applying economic models to issues traditionally outside the realm of economics – what is sometimes pejoratively labeled "imperialism" (see Lazear, 2000) – can also be explained by the apparent substitutability between general and specialized knowledge in the production of research.

## II. Data

### A. *Measures of Ability*

There is obviously no direct measure of the "quality" of a researcher, and a global ranking of scholars would be impossible even if such measures were available, since quality is certainly multidimensional. However, researchers *are* constantly measured against each other by colleagues, university administrators, journal editors, and others using a variety of metrics. These proxies are all flawed in one way or another, but they can provide rough estimates of a researcher's ability, or "general" human capital.

Almost all academic economists (and all the authors sampled in this study) hold doctoral degrees. However, doctoral-granting institutions are not a homogeneous group[5]. Many studies have rated graduate economics departments using a variety of measures. These studies fall into two categories: those that survey opinions regarding departments, and those that measure the publication records of the department's faculty. I use one measure of each type[6].

From the survey category, I use the National Research Council's well-known rankings (hereafter, "NRC"), published in Goldberger, et al (1995), which surveyed economists on the

[4] See Lilla (2001) and Posner (2001) for recent examples of such arguments
[5] Whether more productive students choose to attend those more highly-ranked schools, or whether more highly-ranked schools provide more value added is not crucial here. See Laband (1985) for some evidence on student productivity across departments.
[6] On the differences and relative merits of these two types of rankings, see Beed and Beed (1996), Thursby (2000), Liner (2002), and Laband and Piette (1994).

quality of research produced at randomly selected graduate programs, and from these surveys rated departments on a scale from 0 to 5. From the bibliometric category, I use Scott and Mitias' (1996) rankings of departments by faculty per capita number of pages published in selected journals (hereafter, "SM"). The appendix gives further details on these two measurements.

Using an author's graduate school ranking as a measure of ability or general human capital obviously involves significant measurement error. Moreover, graduates who go on to academic careers and publication in professional journals are a selected sample of graduates from any given university. These measurement errors will tend to bias the results against the findings, however, pushing the estimated coefficients towards zero. Another limitation of graduate school quality as a measure is that most economists employed at major research departments graduated from a small set of very prestigious programs; thus, variability in the explanatory variable may limit extrapolations of these results more generally.

### *B. Measures of Author Specialization*

I use two measures of economists' degree of specialization. The first, which is available for journal articles only, is the degree of specialty of the journal in which a publication is printed. Some economics journals are relatively general, accepting manuscripts for publication from any field in economics. Examples include *Journal of Economic Literature, Journal of Political Economy*, *American Economic Review*, *Economic Inquiry*, and *Economica*. Other journals are more specialized. Examples of this latter class include *Journal of Health Economics*, *Journal of Law and Economics*, *Industrial Relations*, and *Journal of Money, Credit, and Banking*. To measure the degree of specialization for a given journal, I follow a bibliometric standard established by Garfield (1972), and use the fraction of citations a journal's articles receive from the eight journals that cite it the most – the "8-journal concentration ratio", which I calculate from ISI Journal Citation Reports (2000).[7] Journals that are cited by many different journals

[7] All results presented below are robust to the use of a four-journal concentration ratio or a Herfindahl-type index.

tend to be general journals, while journals that are cited primarily by a small number of other journals tend to be more specialized. Table 1 lists the 20 economics journals with the lowest 8-journal concentration ratios.

A second measure of specialization is the number of Journal of Economic Literature (JEL) classification codes assigned to each publication. These codes, assigned by the article's author, in conjunction with the JEL staff[8], are intended to indicate the topic(s) of the publication, and are widely used for this purpose. Hence, by looking at the number of codes listed on a given publication, one can get a sense of its breadth. Since late 1990, JEL classification codes have consisted of one letter, referring to a broad field, and a two-digit number, referring to one of many sub-fields within the letter-field[9]. This measure of specialization allows me to examine non-journal publications, but may be criticized since authors are able to select their own codes to some degree.

### C. *Data Set Description*

A list of all economists who graduated with a Ph.D. between 1990 and 1994 and who were hired by one of 50 selected economics departments between the years 1991 and 1997 was compiled from various editions of James Hasselback's *Guide to Economics Faculty* directories (1998, e.g.), and checked against American Economic Association membership lists published in 1993 and 1997. The 50 selected departments are those listed as the top 50 in the NRC study in terms of research quality. These departments are listed in Table 2[10].

[8] JEL has no "manual" on classifications. Their classifiers include economics graduate, doctoral students and economics professors who memorize the classification system as they begin to use it. Their classifications are checked, and their misclassifications are discussed with them. The person in charge of classification uses this method to maintain a high degree of consistency.
[9] The topical signification of all the letters and numbers can be found in the *Journal of Economic Literature*, or online at http://www.econlit.org.
[10] Every attempt was made to include all appropriate scholars in the dataset, including in some cases personal contacts with departmental administrators and faculty members. The 1991-97 window for hiring was used in order to collect individuals whose first employment after graduate school was with a top-50 department, allowing for at most three years of post-doctoral study. In a few cases, individuals were initially hired by departments outside the top 50 but were later hired by top 50 schools during the sampling period. These individuals were included as well. Nevertheless, it is possible a few individuals were missed.

There were 229 authors for which data was collected. Since Hasselback's directories are of U.S. economics departments only, this excludes economists employed outside of academia, economists employed as faculty in non-U.S. institutions, and economists employed in university academic units other than economics departments.

EconLit, a publication service of the *Journal of Economic Literature*, lists all publications by author in a wide variety of academic journals and presses. The data used in this paper include every publication indexed for each author in the sample. The only exclusions were articles published in working paper series, since these are typically republished in journals or collective volumes, and items published before 1990, of which there are very few in the sample, since all of the authors sampled graduated in 1990-94. A total of 2,730 publications were thus collected.

Figure 1 shows the sample distribution of letter classification codes of publications in sample[11]. Also indicated in Figure 1 is the distribution across letter codes for authors employed at only the top six institutions in the NRC study. The distribution for these authors resembles that for the entire sample closely, although economists at the top six departments seem to publish more research in the fields of labor and health, while publishing less research in the fields of mathematical economics and international economics. Some summary statistics about the sample are given in Table 3.

## III. Empirical Results

Authors may choose their degree of specialization along two margins: the "intensive", or within-publication, margin corresponds to the breadth of topics covered within a given publication by a particular author, while the "extensive", or across-publication, margin corresponds to the breadth of topics covered over different publications by the same author. It is possible to generalize or specialize along one or both margins: one could publish broad papers

[11] Since there are over 600 letter-number classification codes, the sample distribution of these is difficult to observe graphically. Hence, only the sample distribution over the 19 letter codes is given. Diamond and Haurin (1995) document changes in sub-field specialization over time.

encompassing several topics, but always publish on the same topics; alternatively, one could publish many very specialized papers on widely varying topics.

First I consider the intensive margin, as proxied by the 8-journal concentration ratio (CR8) of the publishing journal as a measure of the journal's generality. As discussed above, journals with high concentration ratios tend to be more "specialized". Thus, a negative relationship between graduate school quality and CR8 means that authors with higher ability or general human capital levels are publishing in more general journals.

Also included in these regressions is a measure of the journal's total citedness rate.[12] This regressor must be included because there is a significant correlation between journal generality and journal quality.[13] Other factors that may affect generality are also included as regressors, including the number of co-authors, dummy variables for the year of publication[14] and the author's year of graduation, and fixed effects for the author's publication-contemporaneous employer.[15]

Thus, the results in columns 1 and 2 answer the question: Do authors with higher ability (measured by graduate school NRC score in column (1) and graduate school SM score in column (2)) publish in more generalized journals of the same quality? The results seem to indicate so. In particular, the first column implies that, within the same department, a faculty member who graduated from Berkeley (NRC score 4.554) will publish in a journal with a roughly 4.0% lower CR8 than a faculty member who graduated from Cornell (NRC score 3.562) when the two authors publish in journals of equal quality.

[12] The journals' total citedness rates are the average number of citations per character, as reported in Laband and Piette (1994)
[13] This in itself suggests that specialization and general human capital are inversely related.
[14] Ellison (2002) uses evidence from a few top journals to show that specialization has not increased over time. However, most of the increase in economics publications has been from the introduction of new journals, while the long-established journals have stayed relatively constant in length (Laband and Wells, 1998). In the data used here, it seems unlikely that specialization has increased significantly during the sample period. However, I do find on average that a researcher's degree of specialization tends to decrease a small amount with age.
[15] The fixed effects attempt to hold constant the "quality" of the employer and the type of potential co-authors and facilities available to the author. Exclusion of these fixed effects do not change the coefficients significantly.

Note also that publications with more co-authors do not seem to involve significantly more or less specialization. This suggests that coauthors' specialized human capital may be substitutes instead of complements in the production of research, consistent with previous research on this question by Piette and Ross (1992).[16] As expected, journals with a higher total citedness rate are more general.

In columns 3 and 4, I employ a similar analysis, but use as the measure of specialization the number of different JEL codes listed on the publication. Again, it seems that publications authored by a faculty member graduating from a better department encompass more specialties. The result in column (3) implies that a faculty member who graduated from Berkeley will include 0.29 more codes on average than a faculty member who graduated from Cornell.

Since JEL codes take the form of count data, linear regression may be an inefficient means of estimation. Columns 5 and 6 of Table 4 display results from estimation using a Poisson estimator instead of linear regression (marginal effects at the sample mean are reported).[17] These results are smaller in magnitude than the linear results, but of similar statistical significance.

The results of Table 4 suggest that authors with higher ability or general human capital levels put together more specialties on any given publication (the "intensive margin", as I have called it). A related question is whether they combine more or less specialties *across* different publications, i.e., choose different levels of specialization along the "extensive margin".

To find out, a regression was run at the author level, seeking a relationship between the total number of *different* JEL letter codes listed on *all* an author's publications during the 1991-2002 sampling period and the proxies for ability. Thus, an author who publishes 20 papers, all of which have the same five codes would look relatively general in the previous exercises, but relatively specialized in this exercise. In order to tease out the extensive margin as separate from

[16] Further analysis reveals that differences across journals in quality and generality can explain most of the differences in co-authorship patterns found in the data.

[17] Examination of the means and standard deviations in Table 3 evinces no obvious overdispersion in the data; nevertheless, overdispersion could be problematic. Hence, I also ran these specifications using a negative binomial formulation, and found nearly identical results.

the intensive margin, average number of JEL codes per publication is included as a covariate in each of the regressions.

Table 5 displays the results from these regressions. The left-hand side variable in each column is the number of *different* JEL codes listed on all an author's publications in the sample.[18] The first two columns focus on the number of different letter-number codes, while the third and fourth columns use only the number of different letter codes as the dependent variable.[19] The numbers in the first row of Table 5 may be interpreted to mean that an author graduating from Berkeley would publish in 3.95 more letter-number level fields and 1.45 more letter-level fields over the sampling period than an author graduating from Cornell.

The results of Tables 4 suggest that authors with higher ability generalize on the intensive margin; the results from Table 5 suggest that authors with higher ability also generalize on the extensive margin.

## IV. Robustness Tests

An alternative way of explaining the results in Tables 4 and 5 is that the NRC rating of the graduating institution is partially proxying for the "generality" of the education received there, i.e., better graduate schools provide students not only with higher quality education, but also with broader education. If so, then it would not be a surprise to see that students who graduate from higher-rated schools publish more broadly. On the other hand, this could be considered simply a further implication of the model: abler students attend graduate schools where the education provided is more general.

Nevertheless, to check this possibility specifically, I ran the same regressions as in Table 4, but using a different measure of ability – the quality of the author's *undergraduate* education. To proxy quality of colleges, I use the acceptance rate for the entering 1984 cohort.[20] Other

[18] Since the regressions are run on the author level, employer variables cannot be included, since they vary over any particular author's career.
[19] Year of graduation fixed effects are included, but not reported, in all columns.
[20] The year 1984 was chosen as a typical college entrance year for the faculty in the sample. Data were collected from Peterson's (1986).

proxies, including the fraction of the entering freshmen class from the top 10% of their high school class, or average SAT score evinced similar results.[21] This limited the sample to those authors who graduated from American or Canadian colleges. The quality of the college attended clearly involves further measurement error, as students choose colleges partially based on factors other than quality (e.g., tuition costs and distance from home), but is not likely to be endogenous to the degree of specialization after graduate school. The first two columns of Table 6 give the results of regressions using these measures of college quality as proxies for ability.[22] I find that college quality indeed correlates with more generality, using either measure of generality (although the results are of marginal statistical significance with the 8-journal concentration ratio).[23]

It may also be argued that the existence of tenure in academia affects the results in Tables 4 and 5; for instance, if tenured faculty publish more general articles and those authors graduating from better departments are tenured quicker, this may provide a basis for expecting the inverse relationship between specialization and graduating department quality. The third and fourth columns of Table 6 re-estimate regressions like those in Table 4, but for each author uses only the papers with publication dates prior to his sixth post-graduation year. If tenure is a significant effect, we should see a significantly weaker relationship between graduating department quality and specialization. In fact, the point estimates are slightly closer to zero, but not significantly less. Of course, it may be that untenured authors from higher-ranked graduate schools expect a higher probability of tenure and so begin generalizing even within the first six

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[21] When all three of these measures are included simultaneously, collinearity makes it difficult to tease out the true effects of college quality. Nevertheless, both the acceptance rate and top 10% variables operate in the same direction as found in the analysis here, while the SAT score seems to reduce generality. Further analysis suggests that it is SAT *verbal* score that reduce generality; perhaps students from colleges that have exceptionally high average verbal SAT scores (relative to their average math SAT scores) have a weaker mathematical background upon entering graduate school, and this limits the degree to which they can generalize? In favor of this hypothesis, Paglin and Rufolo (1990) suggest that GRE verbal scores are not strongly related to quality graduate education in economics.

[22] For the sake of brevity, only the results from the intensive margin with the NRC rating measure of ability are shown, though similar results hold for the extensive margin as well.

[23] None of these results change when graduate school quality is included as an additional regressor.

years on this basis; however, insomuch as there is some uncertainty in tenure decisions, there seems to be no evidence of such activity in the data.

A third alternative explanation for the correlation between graduate school rating and generalization is that graduates from top schools have "networks" of graduate school friends who are specialists in other areas. If one is more likely to co-author articles within these networks, then we should see graduates of top schools appearing more general in the data, but only because of the increased options available to them. One of the interesting ancillary results from the previous regressions is the general lack of significance of the number of co-authors in explaining differences in generality. As suggested above, this may indicate that co-authors are substitutes, not complements, in production. However, to test the "networking" hypothesis, we may also consider the question of whether the lack of correlation between co-authorship and generality is a feature of the entire dataset, or if there might be a positive correlation for graduates from the top schools. Empirically, this test may be implemented by including an interaction term between the number of co-authors and the rating of the graduating institution. The fifth and sixth columns of Table 6 give the results of such a test. The lack of a significant coefficient on the interaction terms indicates that there seems to be no difference in the complementarity/substitutability of co-authors across different graduating institutions, though the NRC rating remains (jointly) significant in both regressions.

Table 7 performs four robustness tests specific to the results from Table 5, which considered the "extensive margin" of specialization. In the first column, I perform a similar regression to that in column 3 of Table 5 – using the number of different JEL letter codes over the entire sampling period as the dependent variable, but here I only admit the *first two* JEL letter codes on each publication. Thus, an author who attempted to add additional spurious codes to increase his appearance of generality would not be measured as more general. The results in Table 7 suggest that such gaming does not seem to affect the results much.

The latter three columns in Table 7 consider the possibility that there is a random element to code selection, so that authors with more publications would appear more general. I take three approaches to dealing with this potential problem. First, in column (2) I control for an author's total number of publications. Note that this likely suppresses the true effect, since the major way a researcher may be more general on the extensive margin is by publishing more. Thus, in column (3) I instead exclude authors with fewer than the mean number of publications in the sample (roughly 12, as the summary statistics in Table 3 show), leaving only authors with a large enough number of publications to demonstrate their level of generality. As an third way of dealing with potential randomness in code selection, in the fourth column of Table 7, I only count a JEL code for an author if he has published at least two different articles listing that code. In all columns, the graduate school quality variable remains significant.

**V. Conclusion**

The results presented here suggest those with higher levels of ability or general human capital specialize less. While these findings are suggestive, more research is needed to clarify the factors that influence specialization and its rewards in economics. Moreover, additional research is certainly needed to clarify speculation regarding other fields of study. Of particular interest are fields where specialization is much more pronounced, as in the physical and biological sciences, as well as in research and development more generally. Moreover, some of the methods used in this paper could be used to understand levels of specialization outside of academia, as for instance in the corporate executive labor market, where it is not uncommon for an outside successor to a CEO or CFO to have little or no experience in the new firm's industry.

## Appendix: Graduate School Quality Sources and Issues

### Graduate School Ranking: National Research Council

In 1993, the National Research Council surveyed opinion within many academic fields, including economics (a similar survey was also performed in 1982). Economists at research-doctoral programs were surveyed on their opinions regarding the quality of teaching and research from each of several programs, randomly selected on each questionaire. Respondents were allowed to give each program a score from 0 to 5, with higher scores representing higher quality programs. From these surveys, Goldberger et al (1995) were able to rank 107 research-doctoral programs in economics by their average teaching and research quality scores. I use the research quality scores in this paper, though there is a high degree of correlation between the teaching and research scores in most cases. In comparison to other studies that attempt to rank gradate programs, such as *Gourman's* or *US News and World Report*'s lists, the NRC study was much larger and used a consistent methodology, focusing solely on the opinions of other researchers within the field.[24] Most of the authors in the sample used in this paper graduated from one of the programs rated by the NRC study. However, a few graduated from Canadian or other foreign graduate schools which were not rated by the NRC study.

### Graduate School Ranking: Scott and Mitias

Opinion surveys have limitations. Survey respondents may be biased, out-of-date, or otherwise uninformed. Thus, much of the recent department rankings research has focused on measures of publication success. In this grouping are included rankings based on the number of pages department faculty publish, the number of citations accruing to publications by department faculty, the prominence of faculty publications in journals (lead articles, etc.), and the quality of

[24] Thursby (2000) analyses the NRC data in terms of the relative productivity of inputs and outputs of departments.

journals in which faculty members publish. While in some sense these are more "scientific" measures for department quality and are widely employed, citation practices can in some cases be subjective and uninformed as well (Stigler and Friedland, 1975).

Of the publication-based measures, one of the most comprehensive and widely used is that of Scott and Mitias (1996). That study ranked many U.S. economics departments based on the per capita number of pages faculty in those departments had published in 36 selected economics journals during the period 1984-1992. The number of pages in their study was normalized to *American Economic Review*-equivalent font and page size. Authors were matched to departments by their 1996 employment, not by their publication-contemporaneous employment. Thus, if an author published a paper while employed at department X, that paper was not counted for department X, but for department Y, where the author was employed in 1996. This was done under the assumption that researchers bring their reputations and stocks of knowledge with them when they change employers.

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**Table 1: Twenty Most General Economics Journals, by 8-Journal Concentration Ratio**

| Journal Name | CR8 |
|---|---|
| Journal of Economic Literature | 0.1156 |
| Journal of Economic Perspectives | 0.1240 |
| Economic Journal | 0.1689 |
| American Economic Review | 0.1712 |
| Review of Economics and Statistics | 0.1896 |
| European Economic Review | 0.1942 |
| Economic Inquiry | 0.1989 |
| Journal of Political Economy | 0.2063 |
| Quarterly Journal of Economics | 0.2083 |
| Southern Economic Journal | 0.2114 |
| International Economic Review | 0.2133 |
| Economica | 0.2156 |
| Review of Economic Studies | 0.2235 |
| Brookings Papers | 0.2283 |
| Journal of Labor Economics | 0.2333 |
| Economic Policy | 0.2419 |
| World Bank Research Observer | 0.2518 |
| Journal of Law, Economics, and Organization | 0.2529 |
| Kyklos | 0.2568 |
| World Bank Economic Review | 0.2578 |

**Table 2: Top Fifty Economics Departments,**
**by National Research Council Rankings**

| | |
|---|---|
| 1. Chicago | 26. U. of Washington |
| 2. Harvard | 27. Michigan State |
| 3. MIT | 28. Illinois |
| 4. Stanford | 29. Washington U. |
| 5. Princeton | 30. Iowa |
| 6. Yale | 31. Texas |
| 7. Berkeley | 32. Johns Hopkins |
| 8. Penn | 33. Pittsburgh |
| 9. Northwestern | 34. Texas A&M |
| 10. Minnesota | 35. Ohio State |
| 11. UCLA | 36. Iowa State |
| 12. Columbia | 37. Arizona |
| 13. Michigan | 38. UC-Davis |
| 14. Rochester | 39. SUNY-Stony Brk |
| 15. Wisconsin | 40. USC |
| 16. UC-San Diego | 41. Florida |
| 17. NYU | 42. NC State |
| 18. Cornell | 43. Boston College |
| 19. Cal Tech | 44. Indiana |
| 20. Maryland | 45. Penn State |
| 21. Boston | 46. Rice |
| 22. Duke | 47. George Mason |
| 23. Brown | 48. Vanderbilt |
| 24. Virginia | 49. UC-Santa Barbara |
| 25. UNC-Chapel Hill | 50. U Mass |

**Table 3: Sample Statistics**

| Variable | Mean | St. Dev. | Level of analysis | N |
|---|---|---|---|---|
| Co-authors | 1.75 | 0.701 | Publication | 2730 |
| JEL Codes per publication | 2.25 | 1.07 | Publication | 2730 |
| 8-journal conc. ratio | 0.324 | .0244 | Publication | 1879 |
| JEL letter-number codes used over entire sample period | 14.03 | 8.56 | Author | 229 |
| JEL letter codes used over entire sample period | 5.30 | 2.35 | Author | 229 |
| Grad school NRC rating | 4.47 | 0.307 | Author | 210 |
| Publication pages per faculty at grad school | 40.30 | 13.27 | Author | 211 |
| Total Publications | 11.92 | 8.00 | Author | 229 |
| Journal article | .886 | --- | Publication | 2730 |
| Collective volume article | .108 | --- | Publication | 2730 |
| Book | .004 | --- | Publication | 2730 |

Notes. – Means and standard deviations are calculated at over different levels of analysis to facilitate comparisons. "Publication"-level analysis is over all 2,730 publications sampled. Only articles from journals metered by Web of Science have measured 8-journal concentration ratios, however. "Author"-level analysis is over the 229 different authors sampled. Since some authors attended non-U.S. graduate schools, graduate school quality measures are not available for all authors.

**Table 4: Intensive Margin of Specialization**

Dependent Variables:

| | CR8 | | JEL Codes | | JEL Codes (Poisson) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Grad Institution NRC Rating | -0.04* | | 0.29* | | 0.13* | |
| | (0.01) | | (0.09) | | (0.06) | |
| Grad Institution Publication Pages per Faculty (x 10) | | -0.01* | | 0.08* | | 0.03* |
| | | (0.00) | | (0.02) | | (0.01) |
| Number of Co-authors (x 10) | -0.03 | -0.03 | -0.11 | -0.02 | 0.05 | 0.01 |
| | (0.04) | (0.04) | (0.32) | (0.31) | (0.20) | (0.20) |
| Publication Journal Citations per character (x 10) | -0.02* | -0.02* | | | | |
| | (0.00) | (0.00) | | | | |
| Constant | 0.55* | 0.41* | 0.79 | 1.69* | 0.30 | 0.20 |
| | (0.06) | (0.02) | (0.45) | (0.20) | (0.64) | (0.73) |
| $R^2$ | 0.36 | 0.37 | 0.12 | 0.12 | | |
| N | 1879 | 1887 | 2475 | 2485 | 2475 | 2485 |

Notes. – standard errors in parentheses. * indicates significance at 5% level. "CR8" refers to the 8-journal citation concentration ratio for the publication journal. Year of publication, contemporaneous employer, and graduation year fixed effects are also included in all regressions. There are fewer observations for the CR8 columns because collective volume articles and books are excluded.

**Table 5: Extensive Margin of Specialization**

Dependent Variable: *different* JEL codes over entire sampling period

| | letter-number codes | | letter codes | |
|---|---|---|---|---|
| | [1] | [2] | [3] | [4] |
| Grad Institution NRC Rating | 3.95* | | 1.45* | |
| | (1.70) | | (0.49) | |
| Grad Institution Publication Pages per Faculty (x 10) | | 1.09* | | 0.26* |
| | | (0.39) | | (0.11) |
| Codes per publication | 4.93* | 4.98* | 1.15* | 1.16* |
| | (0.98) | (0.98) | (0.28) | (0.28) |
| Constant | -10.91 | 2.29 | -3.12 | 2.30* |
| | (7.89) | (2.65) | (2.24) | (0.76) |
| $R^2$ | 0.19 | 0.20 | 0.17 | 0.15 |
| N | 210 | 211 | 210 | 211 |

Notes. – standard errors in parentheses. Year of graduation fixed effects included in all regressions. * indicates significance at 5% level.

**Table 6: Robustness Tests for Intensive Margin**

| | college quality as general HC | | only use pubs before tenure | | networking hypothesis | |
|---|---|---|---|---|---|---|
| Dependent Variable: | CR8 | Codes | CR8 | Codes | CR8 | Codes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Grad Institution NRC Rating | | | -0.02* | 0.24* | -0.01 | 0.16 |
| | | | (0.01) | (0.11) | (0.01) | (0.21) |
| College acceptance rate (x 10) | -0.03 | 0.25* | | | | |
| | (0.02) | (0.11) | | | | |
| Number of Co-authors (x 10) | -0.01 | -0.12 | -0.02 | 0.16 | -0.02 | -0.35 |
| | (0.06) | (0.47) | (0.02) | (0.39) | (0.02) | (0.51) |
| Publication Journal Citations per character (x 10) | -0.02* | | -0.01* | | -0.02* | |
| | (0.00) | | (0.00) | | (0.00) | |
| (Grad NRC Rating) X (Number of Co-authors) | | | | | -0.02 | 0.08 |
| | | | | | (0.09) | (0.11) |
| Constant | 0.11* | 1.53 | 0.18* | 0.96 | 0.17* | 1.36 |
| | (0.33) | (1.18) | (0.03) | (0.53) | (0.03) | (0.95) |
| $R^2$ | 0.41 | 0.15 | 0.32 | 0.14 | 0.32 | 0.12 |
| N | 947 | 1243 | 1384 | 1848 | 1879 | 2475 |

Notes. – standard errors in parentheses. * indicates significance at 5% level. Year of publication, contemporaneous employer, and graduation year fixed effects are also included in all regressions.

**Table 7: Robustness Tests for Extensive Margin**

| | 2 Codes only | Control for total pubs | Only high publishers | Only codes used more than once |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Grad NRC Rating | 2.66* | 1.31* | 1.77* | 1.45* |
| | (0.99) | (0.62) | (0.62) | (0.56) |
| Codes per publication | 2.15* | .454 | 1.43* | 1.37* |
| | (0.70) | (0.70) | (0.33) | (0.39) |
| Total publications | | 4.50* | | |
| | | (0.77) | | |
| Constant | -2.86 | -0.72 | -4.61 | -2.20 |
| | (3.01) | (1.21) | (3.13) | (1.72) |
| $R^2$ | 0.16 | 0.20 | 0.19 | 0.17 |
| N | 210 | 229 | 110 | 177 |

Notes. – standard errors in parentheses. * indicates significance at 5% level. Graduation year fixed effects are also included in all regressions.

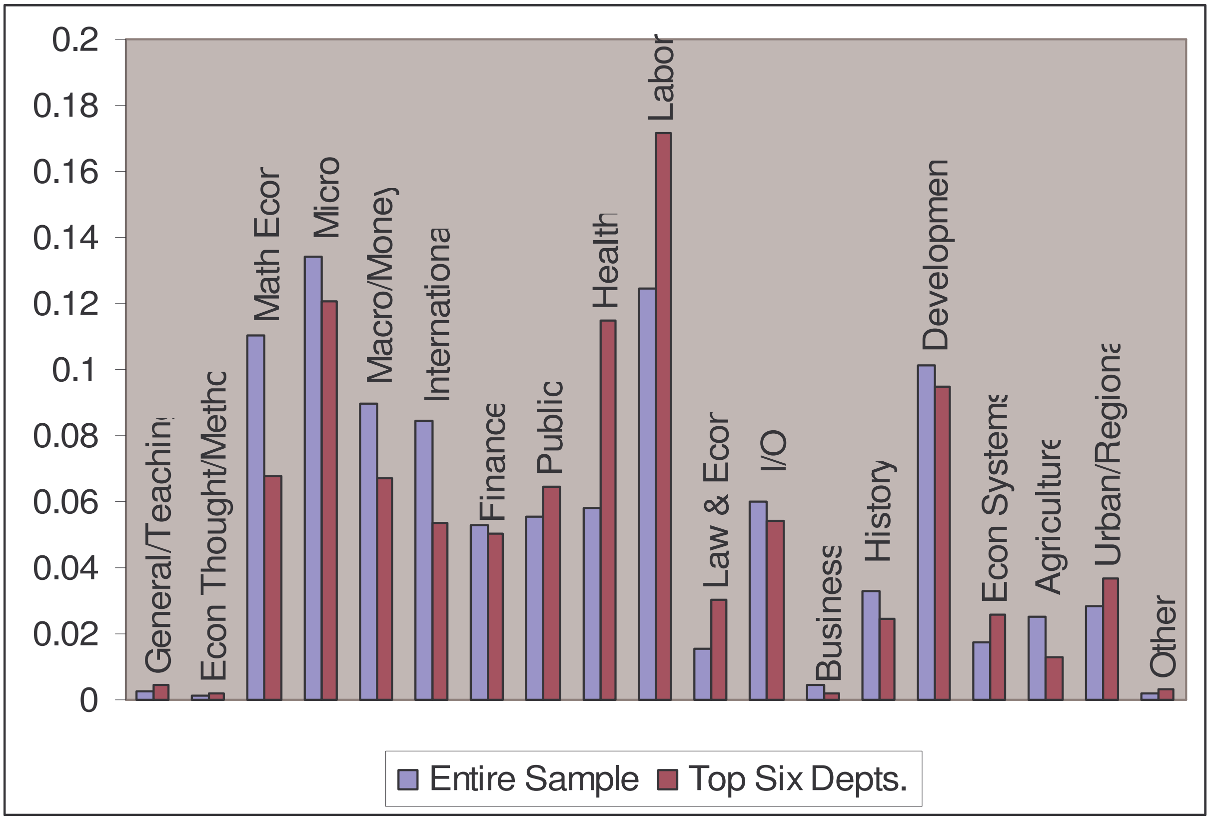


**Fig. 1 – Distribution of JEL Letter Codes**