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Scientists at major and minor universities: mobility along the prestige continuum [1]

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Abstract

This paper investigates the career progress of scientists at 'major and minor universities' once they have chosen to participate in the development of an emerging field, posing three fundamental questions: (1) are scientists who are involved in the early stages of a field's development and who persist more likely to graduate from more prestigious universities? (2) In an emerging field, do graduates from prestigious universities pursue career paths that differ from the ones pursued by their peers from less prestigious institutions? (3) Are graduates from prestigious universities who choose academic careers more likely to find employment at prestigious universities?

Empirical evidence is provided on the career progress of 373 scientists working in the field of neural networks, graduating from US universities. The prestige of a scientist's graduate school is found to be a significant indicator of the prestige of his or her academic appointment in the initial five years after graduation. Beyond five years, the effect of graduate school prestige becomes non-significant. Whether one entered the field before or after it gained widespread legitimacy in the scientific community apparently does not affect subsequent career progress in terms of institutional prestige.

1. Introduction

Given sociologists' interest in occupational and career patterns [15,25,45], it is not surprising that the scientific profession has received close scrutiny [2,14,17,26]. Indeed, numerous aspects of the sociological dynamics of a scientist's career have been examined, but perhaps none more closely than the determinants of career advancement along the prestige continuum of research institutions, the so-called major and minor universities

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[14,16]. How much of career success is attributable to the intrinsic quality of a scientist's research accomplishments as reflected in published work? Or, are other more 'particularistic' factors at work? For example, how important is the institutional prestige of one's doctoral degree granting university, the standing of one's thesis supervisor in the scientific community, and the socio-economic status of one's family? The origins of many of these investigations can be traced back to the Research Program in the Sociology of Science initiated at Columbia in the late 1960s.

A considerable amount of effort has been directed toward understanding the relative influence of individual productivity and accomplishment versus particularistic criteria in determining who receives academic appointments at the most prestigious departments and institutions. Although the results are sometimes contradictory [14], the empirical evidence usually confirms the importance of institutional prestige. For example, studies by Hargens and Hagstrom [18] and Cole and Cole [6], find that an individual's accomplishments are as important as academic background in securing a prestigious academic appointment. Crane [7,9] and Long [25] find that the prestige factor, both in terms of degree granting university and graduate supervisor, is significantly more influential than research accomplishments in securing a position. In reviewing the evidence from both streams of research, Finkelstein [14] is led to conclude that "... at the time of initial appointment, it is much more the prestige of one's terminal degree and one's graduate sponsor than one's scholarly productivity which will lead to a good academic appointment."

Turning the question around, some investigators suggest that the prestige of an academic department may be an important factor contributing to a scientist's productivity [1,18]. Although Hargens and Hagstrom [18] are unable to show that institutional standing influences productivity on the individual level, they do provide evidence on the aggregate level. Furthermore, Cole and Cole [6] and Long [25] find that institutional prestige may be nearly as important as research performance, while Crane [7] finds institutional prestige more important than research performance in determining the amount of recognition (in terms of rewards, honors, and citation frequency) that accrues to a scientist.

In the present paper we investigate further the significance of institutional stratification within the scientific community as it relates to the inclination of scientists who are involved in an emerging and unconventional field of research. In particular, we examine three questions. (1) To what extent are scientists who are involved in the early stages of a field's development and who persist more likely to graduate from more prestigious universities? (2) In an emerging field, do graduates from prestigious universities pursue different career paths in terms of employment sector (academic, industry, government) within the scientific community? (3) Are graduates from prestigious universities who choose academic careers more likely to find employment at prestigious universities and, does it matter whether they enter the emerging field before or after it has gained legitimacy within the scientific community?

Unlike earlier sociological studies, we intend to focus specifically on scientists who enter a field early, before it is widely accepted by the rest of the scientific community. By 'early entrants,' we mean those scientists who initiate and continue working in a field before it is widely recognized as significant, or perhaps even legitimate, by their peers. Empirical evidence suggests that such scientists, statistically speaking, are relatively rare: although the probability of a scientist remaining with a given field of research increases the longer he or she stays with it, the likelihood a scientist will persist more than a few years is fairly low [41,42]. Despite their scarcity, the scientists who enter a field early are essentially the catalysts behind change in science. By virtue of their unconventional problem choices and unrelenting determination, they may ultimately lead the way in creating a new research specialty. While we have isolated early entrants for in-depth examination, in doing so we nonetheless do not mean to underestimate the significance of contributions to a field made by scientists who follow afterward.

Institutional stratification within the scientific community raises an interesting question with respect to scientists who enter a field early. It may very well be that the relative stature of a university has some relevance in the pioneering behavior of its faculty and students, what might be called the 'backwater hypothesis.' On the one hand, prestigious research universities may have the resources that would enable those scientists who are inclined to take chances more readily to explore new fields. On the other hand, the prominence of such institutions may tend to reinforce among their scientists a more cautious attitude toward doing science that extends rather than challenges conventional thinking. It is not uncommon that in the early stages of emergence, radically new streams of research lack legitimacy within the scientific community. Unable to convince their mainstream colleagues, some scientists may seek haven at lesser known institutions in order to pursue their unconventional research. In the same vein, one might extend the argument to ask whether students who pursue pioneering research agendas are any more or less likely to obtain positions at prestigious universities upon graduation.

The case of 'cold fusion' research provides a recent illustration [28]. Setting aside the issue of whether or not cold fusion has merit, the events surrounding this discovery exhibit how institutional prestige may play a role in the way scientists approach unconventional research. The remarkable claims of cold fusion, and the subsequent efforts to confirm it, quickly degenerated into a major scientific controversy pitting those scientists who found evidence of its effect against those who saw it as spurious, if not scandalous. Through the course of the debate, undercurrents of elitism emerged among some scientists. The suggestion was that reports which confirmed cold fusion were more likely to come from lesser known institutions. What is most interesting is that such perceptions did not actually fit the reality. A close examination of the record shows little if any correlation between institutional prestige and the propensity to confirm cold fusion research [28]. Nevertheless scientists are mindful of perceptions. Cold fusion is a cautionary tale that underscores how issues of institutional prestige can become muddled in scientific debates.

2. The neural network research community

In order to examine these questions empirically, we take as the basis of this paper a recent international survey we conducted of more than 700 scientists working on the development of neural networks. A neural network is a type of information processing system that is inspired by models of the human brain. By using a biological model in its design, a neural network system has certain features that make it unique in form and function from conventional computers. For example, a neural network is not programmed in the usual sense, but rather it is trained with data. This implies that the computational performance of a neural network improves with experience: as it processes more and more information in performing a task, it becomes increasingly more accurate in its response.

Another distinctive feature of a neural network is its degree of parallelism in processing a task. Unlike a normal computer with a single or small number of sophisticated central processing units, a neural network has a very large number of simple processing elements that operate simultaneously on a computational problem. These features allow it to perform certain tasks that otherwise might be very difficult using existing computer technology. Neural networks are also referred to as connectionist systems, adaptive systems, or neurocomputers [10].

Neural networks have a considerable history of development, stretching back to theoretical explanations of the brain and cognitive processes proposed during the 1940s. In the early years, scientists formulated and elaborated basic models of neural computing that they then used to explore phenomena such as adaptive stimulus–response relations in random networks. By the 1960s there were several efforts to implement neural networks, the most notable being the single-layer 'perceptron.' Among neural network scientists the perceptron was considered a watershed [3,23,44], but at the same time it served as a lightning rod for criticism from scientists more interested in the burgeoning field of artificial intelligence [21,29,30,37]. The idea of neural networks, as exemplified by the perceptron, quickly became seen as almost antithetical to the symbolic reasoning principles of artificial intelligence. Critical analysis of the perceptron led Marvin Minsky and Seymour Papert [29], both highly respected AI scientists, to proclaim that the concept was fundamentally flawed, and as such, inappropriate for scientists to waste much effort on. By casting doubt as to its legitimacy, antagonists of neural networks may have effectively dissuaded other scientists from entering the field in larger numbers [21,30,37].

The controversy surrounding neural networks notwithstanding, work continued during the early 1970s. An analysis of the literature shows that no more than a few hundred scientists worldwide were active in the field during that period. For more details on these analyses, we refer to our earlier work [11,38]. Undeterred in their belief of the potential of neural networks, their persistence over the next decade eventually paid off. By the 1980s, neural networks began to be viewed in a new light by scientists in a variety of disciplines, so that the field soon achieved a position of legitimacy within the scientific community [3,10, 44]. A professional society for neural network scientists was formed, specialized journals and books were published, and the first in a series of international conferences were held.

While it is difficult to explain exactly why perceptions of the field changed so dramatically, at least four important technical events can be discerned: (1) the evolution of the single-layer perceptron into a multi-layer system; (2) the rapid development of related technologies that enabled scientists to develop, simulate, and diagnose neural networks of greater sophistication; (3) significant progress in theoretical understanding of neuro-biological processes; and (4) the contributions of scientists pursuing the idea of parallel distributed processing, the so-called PDP-group. In light of these developments, as well as others, interest in the field became widespread, so that the number of scientists working on neural networks expanded rapidly [20]. By the end of the decade the size of the field swelled in membership from a few hundred to several thousand scientists worldwide [38].

The evolution of the neural network research community is not unusual and may even be typical of emerging fields in some of its social characteristics. From our research, we have found that it is fairly common for new fields to lack widespread acceptance for long periods, sometimes attracting controversy, other times simply being ignored by scientists [4,5,8,13,19,24,27]. But when they do catch on, fields tend to grow rapidly. This pattern has occurred, to greater or lesser extent, in several fields we have examined (e.g. the development of cochlear implants [41], catalyst development for epdm rubber and polypropylene [42] or the development transgene plants [12]). Given the recent experience within the neural networks research community, this case presents us with an opportunity to examine in great detail the experience of early entrants into the field relative to large numbers of scientists who follow in their footsteps.

As argued, in this paper, we want to focus especially on the relationship between the institutional prestige of a scientist's graduate school and the prestige of his or her current academic employer taking into account whether the field was entered before or after it attained legitimacy within the scientific community. It should be noted then that the subject of the paper is not on the 'problem of problem choice.' Problem choice behavior among scientists in an emerging field is determined by multiple influences [31,39,47] that exceed the specific focus of this paper.

3. Method and data: measuring institutional prestige

The empirical data for this paper were collected during an earlier international survey of neural network researchers. The methodology and the internal validity checks for this survey have been reported extensively [11,38,39]. It is obvious that the survey data pertain to one specific technological community. This limits the external validity of the findings. Ideally, one should study the issues raised irrespective of research field. However, given the exploratory nature of the questions addressed in this paper, these external validity issues are deemed subordinate to internal validity requirements.

For the present analyses, we rank-order the universities in our survey database according to an index of institutional prestige. We use as the basis of our index the citation and publication data on US universities, which was compiled by Small [46] and his colleagues at the Institute for Scientific Information and recently used by the Office of Technology Assessment [36] to rank US universities. Citation impacts scores (i.e. the ratio of total citations to total papers published [1]) have been implemented in a variety of studies to measure the relative eminence of a scientist [33] and prestige of academic departments [43], a laboratory's research performance [32,34], and the competitive stature of a country's scientific community [35].

The statistics compiled by the Institute for Scientific Information contain the cumulative number of publications and citations for each US university over the period 1973–1988. We use the citation impact score of publications for each university over this period as a (continuous) proximate measure of institutional prestige. An examination of the rank-order of the top 100 US research universities suggests that citation impact scores have good face validity as a measure of institutional prestige (see Small [46]). Nonetheless, it is important to recognize that this measure pertains to the university as a whole and not to the prestige of individual departments, which can vary widely in a given university. The score also does not reflect institutional prestige that may arise from criteria other than research performance such as excellence in teaching, for example.

Because the validity of making international comparisons with citation impact scores is not well-established, the present analysis is limited to researchers who graduated from US academic institutions. To this end, we used a sample of 373 respondents, the large majority of whom ($N=348$) are currently employed within the US. Most of the 25 respondents who were educated in the US but no longer reside there, left the country upon graduation. At the time the survey was conducted, 22 of them held posts at foreign universities. For the 348 respondents who were educated and reside in the US, 207 (59%) are employed in academic labs, 103 (30%) reside in industrial laboratories, and 38 respondents (11%) are employed in non-academic, not-for-profit institutions, primarily government laboratories. The sector distribution of respondents does not differ significantly from that of the original sample ($\chi^2 = 3.35$, n.s.).

For each of the 373 US-educated respondents in the sample we compute a citation impact score for their *graduate* school. There are a total of 104 universities represented in the sample. Using the ISI data, we also compute an institutional prestige measure for each respondent's *current* academic employer (in all cases but two). The respondents hold appointments at 86 different US universities. We do not calculate institutional prestige scores for industrial employers. Although industry data exist, their adequacy as a measure of prestige for industrial labs requires closer inspection, which is beyond the scope of the present study. As a result, there is a total of 205 respondents for whom we calculate prestige measures both for their graduate school and for their current academic employer.

The continuous measure of prestige is used to create an ordinal variable. The 125 universities (graduate schools and current employers) are divided into 20% intervals, thereby creating five equal ranks. The 25 institutions in the top 20% interval have citation impact scores in excess of 16.3. The 20–40% interval have scores ranging from 13.5 to 16.2. The 40–60% interval have scores between 10.6 and 13.5. The 60–80% interval have scores between 8.1 and 10.5. The 25 remaining institutions have citation impact scores below 8.1.

The distribution of respondents by prestige of graduate school and by prestige of current academic employer is shown in Table 1. Both sets of academic institutions considered in this table have a mode in the top 20 category. Inspection of the median values for both distributions further indicates that the majority of respondents are in the

[1] The continuous prestige index is computed as follows (with P_i = prestige score for academic institution i):
$P_i = (\Sigma_{1973}^{1988}\text{ citations})_i / (\Sigma_{1973}^{1988}\text{ publications})_i$.

Table 1
Distribution of respondents in terms of the ranking of their graduate school and in terms of the ranking of their current academic employer (*median*)

University rank	Graduate school		Current institution	
	N	%	*N*	%
First 20%	131	35.1	61	29.8
Second 20%	*108*	*29.0*	*56*	*27.3*
Third 20%	69	18.5	33	16.1
Fourth 20%	41	11.0	31	15.1
Fifth 20%	24	6.4	24	11.7
Column totals	373	100.0	205	100.0

Three hundred and seventy three respondents obtained their graduate degree at a US university. Of them, 250 are currently employed at a US university. Prestige indices were computed for US academic institutions only.

top categories as far as institutional prestige is concerned.

4. Scientists at major and minor universities and early entry to the field

According to a classification scheme previously developed and reported, we classify respondents as early or late entrants depending upon when they entered the field [11,38,39]. In short, early entrants are those scientists who begin research in a field before it obtains widespread legitimacy within the scientific community. After a careful historical and statistical analysis of the field of neural networks, examining many different factors and testing for sensitivity, we divided the sample into early and late entrants using 1984 as the transitional year. There is nothing inherently significant about this year, in particular. Indeed, we could have chosen any year between 1980 and 1984. We tested the sensitivity of selecting 1984 as the cut-off year by performing a discriminant analysis on the core survey items. The results indicate that the categorization scheme is robust.

By demarcating the sample into two periods, we do not mean to imply that the field's transition to legitimacy was instantaneous; we do so simply to preserve cases for the statistical analysis. None the less, something, or, perhaps, many things, unmistakably happened in the early 1980s that transformed neural networks from a curiosity and the object of skepticism to a major interdisciplinary stream of research [3,44]. An examination of the scientific literature and discussions with neural network scientists also supports our selection of 1984. Prior to 1980 there were no more than a few hundred neural network scientists worldwide; after 1985, the neural network community grew many fold, so that today there are several thousand scientists working in the field [20].

Table 2 shows the distribution of respondents by rank (graduate school and current employer) according to our classification of early and late entry. Among the 373 respondents present in the sample, 76 (21%) entered the field of neural networks prior to 1984; 287 respondents entered the field since 1984 (79%). Ten respondents did not specify the year they started their neural

Table 2
Institutional rank-order distributions for early and late entrants (*median*)

University rank	Graduate school				Current institution			
	early entrant		late entrant		early entrant		late entrant	
	N	%	*N*	%	*N*	%	*N*	%
First 20%	31	40.8	96	33.5	10	23.3	51	32.5
Second 20%	*21*	*27.6*	*85*	*29.6*	*12*	*27.9*	*42*	*26.8*
Third 20%	17	22.4	51	17.8	9	20.9	24	15.2
Fourth 20%	6	7.9	34	11.8	9	20.9	22	14.0
Fifth 20%	1	1.3	21	7.3	3	7.0	18	11.5
Column totals	76	100.0	287	100.0	43	100.0	157	100.0
Mann-Whitney test	$z = 1.57$, n.s.				$z = 0.87$, n.s.			

Total *N*s differ from the ones reported in Table 1 due to missing values on the entry period variable.

network activities. No statistically significant differences are apparent between early and late entrants as far as the distributions of graduate school rankings and current academic institution rankings are concerned.

We further classify respondents according to their educational status at the time they began neural network research: that is, pre- or post-receipt of their highest academic degree. For simplicity, we will refer to pre- and post-degree respondents as 'students' and 'graduates,' respectively. In the present sample, 162 respondents (45%) are classified as students when they entered the field; 169 respondents (47%) are classified as graduates. In order to avoid ambiguities, we omit 29 respondents (8%) who obtained their highest degree in the year they entered the field of neural networks. Of the early entrants 66% were students (principally pursuing doctoral degrees) when initiating work in neural networks, in comparison to about 44% of late entrants. Table 3 shows the distribution of respondents by rank of graduate school, comparing early and late entrants according to their educational status when entering the field.

Mann-Whitney tests, comparing the distribution of students and graduates within each group, indicate significant differences among both early and late entrants. About 48% of early entrants who entered the field prior to receiving their highest degree graduated from a top-ranked university. This is not true for early entrants who entered the field once they obtained their highest degree ($P < 0.05$). As far as late entrants are concerned, however, slightly less than 40% of the respondents who entered the field after graduation obtained their highest degree from a top-ranked university. About 16% of late entrants who entered prior to graduation hold degrees from institutions with the lowest rank ($P < 0.05$).

It is interesting to note that the lower-ranked institutions (fourth-20 and fifth-20) become visible in the sample only after the field attains widespread legitimacy. A further analysis of the students among late entrants shows that, of the 15 respondents in the fourth-20 rank, 80% were students at the time of the survey. For the 18 respondents in to the fifth-20 rank, 56% were in the process of obtaining their highest degree at the time of the survey.

The disproportionate representation of students among early entrants at top-ranked universities in the respondent sample may also be the consequence of time-dependent processes. Given the time span of the field's emergence, scientists (regardless of their educational status at the time they began neural networks research) who graduated from universities of lesser rank during the early years may have moved on to other research agendas. As a consequence, their lack of persis-

Table 3
Institutional rank-order distributions for early and late entrants according to their educational status at the time they entered the field (*median*)

Rank graduate school	Early entrants				Late entrants			
	student		graduate		student		graduate	
	N	%	*N*	%	*N*	%	*N*	%
First 20%	22	47.8	7	29.2	33	28.5	54	37.2
Second 20%	*14*	*30.4*	*7*	*29.2*	*39*	*33.6*	*37*	*25.5*
Third 20%	10	21.8	6	25.0	11	9.5	33	22.8
Fourth 20%	0	0.0	4	16.6	15	12.9	18	12.4
Fifth 20%	0	0.0	0	0.0	18	15.5	3	2.1
Column totals	46	100.0	24	100.0	116	100.0	145	100.0
Mann-Whitney test	$z = 2.07$, $P < 0.05$				$z = 1.83$, $P < 0.05$			

Student: respondents initiating neural networks *prior to* receiving highest degree. Graduate: respondents initiating neural networks *after* receiving highest degree. Respondents starting neural network research in the *same year* they graduated were omitted.

tence in the field may have led to their exclusion from the survey population as early entrants. If this is the case, then top-ranked universities produce scientists with a higher commitment to their chosen research agenda than lower-ranked institutions. But to be certain, we must test this hypothesis using a longitudinal research design, which is now being conducted.

Additional Mann-Whitney tests comparing early and late entrant graduates do not yield a statistically significant difference ($z = 0.63$, n.s.). However, when we compare early and late entrant students, we find the difference to be highly significant ($z = 3.08$, $P < 0.01$): early entrant students are more likely to graduate from top-ranked universities than are students who are late entrants.

A final word of caution is warranted. The disproportionate representation of early entrant students relative to graduates may be another consequence of time-dependent processes. Since graduate early entrants are, on average, about ten years older than student early entrants when they enter the field, their numbers (and hence representation in the sample population) are likely to be diminished to some degree by retirement. As a result, graduates who entered early may be slightly underrepresented in the respondent sample. None the less, the fairly large disparity in representation between students and graduates would be difficult to explain by retirement alone.

5. What happens after graduation?

Now that we have an insight into the graduate school distributions of early and late entrants, the next question is: what happens to respondents after they receive their highest degree? Do they pursue academic careers or do they seek employment in another sector of the scientific community? Furthermore, what is the nature of mobility along the continuum of institutional prestige, and how does mobility relate to the conduct of pioneering research? Specifically, what are the consequences of entering a field early in terms of a scientist's ability to secure an initial appointment after graduation?

Table 4
Prestige of graduate school versus sector of current employment ($N = 281$)

Rank graduate school	Current sector of employment		
	academia	industry	government
First 20	64	33	13
Second 20	47	24	3
Others	51	32	14
Column totals	162	89	30

Pearson $\chi^2 = 5.50$, d.f. = 4; n.s.; Kruskal-Wallis one-way ANOVA: $\chi^2 = 0.61$, n.s. N differs from the original sample of 373 because students (whose graduate school equals their current employer by default) are omitted.

We use the ordinal prestige rankings to investigate the inter-sector mobility of graduates from major and minor universities. In order to facilitate the analysis, we collapse respondents into three categories: those who graduated from (1) top 20% institutions, (2) universities in the second 20% interval, and (3) all other graduate schools. This aggregation is necessary to alleviate the potential for cell size problems in some of the non-parametric statistical tests used in this section. Furthermore, to avoid any ambiguity, respondents in the process of obtaining their highest degree or graduating at the time of the survey are omitted from the analysis.

As demonstrated in Table 4, no statistically significant differences are found with respect to the respondents' current sector of employment: graduates from major universities show a sectoral distribution pattern which is highly similar to that of their colleagues from minor universities. Furthermore, for each sector of employment, the respondent distributions which are based on the rank of their graduate school are not significantly different.

Introducing the early/late entrant dichotomy does not modify the conclusions discussed in Table 4. Detailed contingency table analyses do not allow us to reject the null hypothesis of independence between graduate school prestige and current sector of employment for both early and late entrants. This result was further confirmed by fitting an unsaturated loglinear model to the data using the three-way sectoral classification, the three-way ordinal prestige classification, and the dichotomous early/late entry classification as parameters. If the variables are independent, they can be represented by a loglinear model that does not have any interaction terms [22]. Thus, in our case the independence model looks as follows:

$$\log \hat{F}_{ijk} = \mu + \lambda_i^{\text{entry}} + \lambda_j^{\text{sector}} + \lambda_k^{\text{prestige}} \qquad (1)$$

where $\hat{F}_{ijk}$ is the expected frequency in the (i, j, k)th cell based on the model. Two iterations are required for convergence. The standardized residuals are well below ± 1.96, indicating no substantial discrepancies between the model and the data. Furthermore, inspection of the normal probability plot does not show the distribution of the standardized residuals to deviate substantially from a normal distribution. The likelihood-ratio χ^2 statistic for the independence model is 15.7 (d.f. = 12, $P = 0.21$). The Pearson χ^2 statistic is 13.5 (d.f. = 12, $P = 0.33$). The results do not allow us to reject the independence model and thus confirm the contingency table analyses.

Due to empty cells, we cannot include the educational status of the respondent at the time of entry as a fourth parameter in the independence model. We do, however, repeat the analysis with the three-way sector classification, the three-way ordinal prestige classification, and the dichotomous student/graduate classification as parameters in an unsaturated independence model similar to Eq. (1). The result is comparable to the one obtained with the previous model: likelihood-ratio $\chi^2 = 15.4$ (d.f. = 12, $P = 0.22$) and Pearson $\chi^2 = 13.2$ (d.f. = 12, $P = 0.36$). Once again, we are unable to reject the independence model. Inspection of the standardized residuals reveals no problems related to normality. This result is to be expected from detailed contingency table analyses: the sectoral patterns shown in Table 4 remain consistent when studying respondents who enter the field as students versus respondents who enter after graduation.

To conclude, the prestige of one's graduate school does not appear to be an important determinant of a respondent's current sector of employment. Whether a respondent is a graduate from a top-ranked university or not, or whether a respondent is an early entrant or not, does not lead to significantly different employment sector patterns upon graduation. For instance, the empirical evidence presented here does not suggest that a graduate from a top-ranked institution is more likely to stay in academia than a graduate from an institution of lesser rank. This result holds for early as well as late entrants. These findings, of course, warrant further scrutiny. More specifically, we are interested to see what happened to those respondents who stayed in academia: what is their mobility along the prestige continuum?

6. Mobility along the prestige continuum

In this section we examine the relative difference in prestige ranking for a respondent's graduate school and his or her current employer. We limit the analysis to the 205 respondents who have academic appointments. The Pearson correlation coefficient between the prestige of one's graduate school and the prestige of one's current academic employer is 0.56 ($P < 0.001$; $N = 205$). This finding reaffirms prior sociological research on the relationship between the prestige of one's graduate institution and the chance of becoming employed at a prestigious academic institution. After adjusting the data by removing students and recent graduates, the remaining sample has a 0.40 ($P < 0.001$; $N = 139$) correlation between graduate school prestige and the prestige of current academic affiliation.

In order to study mobility along the continuum of institutional prestige in greater detail, we compute the change in institutional prestige between one's current academic employer and his or her graduate school for each respondent using the continuous prestige measure (see Table 5). In comparison to late entrants, the data indicate that early entrants realize a much greater decrease in their institutional prestige ranking (a marginal mean of -3.37).

In order to understand the possible meaning of this result, we employ a two-factor analysis of co-variance with the continuous differential prestige variable as a dependent variable and the

Table 5
Average changes in prestige of academic affiliation for early and late entrants according to their educational status at the time they entered the field ($N = 120$)

	Early entrants	Late entrants	Marginal means
Student	-3.03 ($N = 24$)	0.77 ($N = 19$)	-1.35
Graduate	-3.98 ($N = 13$)	-0.96 ($N = 64$)	-1.47
Marginal means	-3.37	-0.56	-1.43

Prestige change is calculated as: prestige of current employer minus graduate school prestige. Respondents being students at the time of the survey or starting their neural network research in the year they graduated are omitted from the analysis. Only researchers who are currently with US universities are included. Hence the sample size reduction from 205 to 120.

Table 6
Two-factor ANCOVA on changes in prestige of academic affiliation for early and late entrants according to their educational status at the time of entry ($N = 120$)

Variables in the analysis	d.f.	F	P
Professional experience (covariate)	1	8.05	0.005
Early/late entrant (independent variable)	1	3.41	n.s.
Student/graduate (independent variable)	1	0.09	n.s.
Interaction (between independent variables)	1	0.08	n.s.

Respondents being students at the time of the survey or starting their neural network research in the year they graduated are omitted from the analysis. Only researchers who are currently with US universities are included.

early/late and student/graduate dichotomies as independent variables (see Table 6). Our choice of independent variables follows from the previous analysis. The time elapsed since the respondent's graduation (i.e. years of professional experience [2]) is used as a covariate. (It would be preferable to use the respondent's year of initial employment at his current academic affiliation to compute this covariate. Although we inquired in the survey about the date of initial employment, there are a large number of missing values thereby yielding cell sizes that are too small for statistical analysis. As a consequence, we use professional experience at the time of the survey as a proximate covariate.) By this definition, it is assumed that students have not yet accumulated professional experience.

As shown in Table 6, changes in institutional prestige between graduate school and current academic employer can largely be explained as a function of the time elapsed since obtaining one's highest degree. The raw regression coefficient for the covariate is -0.155 ($P = 0.005$), which suggests a decrease in institutional prestige as the respondent's professional experience increases. The respondent's educational status when entering the field of neural networks does not exert any main effects, nor do there appear to be any statistically significant interaction effects. In comparison to late entrants, scientists who entered the field early are more likely to be employed at institutions that are less prestigious than their graduate schools were. However, when controlling for professional experience, the first-order difference is not significant. Thus, the early/late entry dichotomy does not help us to explain differences in institutional prestige: early and late entrants to the field experience similar decreases in institutional prestige as they progress in their career.

Repeating the two-factor ANCOVA with the respondents' age as a covariate yields results similar to that reported in Table 6. The independent variables do not show any statistically significant interaction effects nor main effects. The age covariate is statistically significant ($P = 0.004$) and has a negative regression coefficient (-0.165). The correlation between professional experience and age is 0.89 ($P < 0.001$).

The relationship between graduate school and the prestige of one's current employer is further investigated by classifying respondents into four cohorts based on professional experience: 1 to 5 years, 6 to 10 years, 11 to 15 years, and more than 15 years. This enables us to test the relationship between prestige of graduate school and prestige

[2] Professional experience is defined as the time elapsed since the receipt of one's highest degree. Professional experience at entry is then measured as the number of years between the receipt of one's highest degree and the year one entered the field of neural networks. Professional experience at the moment of the survey is measured as the number of years elapsed since the receipt of one's highest degree in the year the survey took place, i.e. 1990.

Table 7
Regressions for current affiliation prestige (D.V)

Professional experience	Constant	Prestige of grad. school	Early (1)/late (0) entrant	adj. R^2	F
1–5 years ($N = 49$)	5.85 ** (1.9)	0.65 *** (0.1)	−1.86 (1.5)	0.39	15.8 ***
6–10 years ($N = 30$)	10.54 ** (3.2)	0.17 (0.2)	−0.21 (2.1)	0.00	0.33
11–15 years ($N = 23$)	7.96 * (3.5)	0.42 (0.2)	−0.28 (2.0)	0.07	1.89
More than 15 years ($N = 28$)	7.63 * (3.6)	0.40 (0.2)	−2.20 (1.8)	0.07	2.0

* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$ (standard errors in parentheses). Respondents being students at the time of the survey are omitted. Only researchers who are currently with US universities are included.

of current employer within each cohort with a regression model. The prestige of the respondent's current academic affiliation is the dependent variable. A dummy variable is included in the model to test the relevance of a respondent's status as an early (value = 1) or late entrant (value = 0). Admittedly, as with the previous ANCOVA, it is preferable to use the respondent's initial year of employment at the current academic affiliation to compute the covariate. Cohorts could then be based on the time between a respondent's graduation and first year of employment at the current academic employer. Instead we use professional experience at the time of the survey as a proximate covariate.

Table 7 shows that only the model for the first cohort is statistically significant: institutional prestige of graduate school is highly significant for respondents within 1 to 5 years of graduation. Beyond five years, graduate school prestige is no longer a good predictor of the institutional prestige of a respondent's current employer. Although the regression coefficient of the early/late entrant dummy variable is always negative, it never attains statistical significance, thus confirming the previous ANCOVA results.

7. Discussion and conclusion

The relative prestige of a university within the scientific community is an important consideration when it comes to choosing a doctoral program. While a number of factors may enter into their decisions, the reputation of a university is likely to weigh heavily on the minds of prospective doctoral students. With institutional prestige comes access to an abundance of human and physical resources necessary to conduct leading-edge research. Moreover, the centrality of prestigious universities provides a level of visibility to scientists within the scientific community that can be instrumental to establishing the legitimacy of a research agenda. Institutions also benefit from their relative standing precisely because they are able to attract highly qualified students, who in turn reinforce the overall research capabilities of a university. One need only listen momentarily to a university dean or provost to realize the weight of a school's ranking among its peer institutions.

Clearly, institutional prestige matters, to students, to faculty and to university administrators. Nonetheless, the benefits of prestige may come with a cost in terms of scientific innovation, since the next most important objective to having a good reputation is maintaining one. However, when it comes to pioneering new fields of science, it is often necessary for scientists to take career risks: to risk that their unconventional ideas will not bear fruit, that no other scientists will follow their lead, or that their efforts will be seen as misguided by colleagues. Does the pressure of protecting an institution's standing reduce the incentives to scientists for pursuing unconventional research directions? Or, conversely, among lesser known institutions, does the desire to attain a higher standing lead scientists to take risks that others might not otherwise consider?

In the case of neural network scientists the evidence is mixed. Comparing the distribution of respondents across the prestige continuum we find no significant difference between scientists who entered the field early and those who followed them. However, when we divide the sample according to whether or not the respondent initiated work in the field of neural networks prior to receiving his or her highest degree, we find some interesting differences. First, among early entrants, respondents who are students when they start neural network research are more likely to be doing their graduate work at universities of higher prestige, than those who initiate neural network research after receiving their highest degree. Second, among respondents who are students when entering the field of neural networks, early entrants do their graduate work at more prestigious universities than do late entrants. Thus, we find 'pioneering' behavior to be most prevalent among respondents who are students (at the time they start neural networks research) at the more highly ranked universities.

Examining the career progress of respondents, we find that over time scientists tend to move from relatively more prestigious universities to less prestigious universities. This pattern occurs regardless of whether a respondent is an early or late entrant or whether he or she is a student when entering the field of neural networks. The relevance of such a finding can be seen in the premium that prospective doctoral students place on starting their career at a highly ranked graduate school. When comparing early and late entrants, we find that scientists who enter the field early are less likely to receive an appointment at an institution matching the prestige of their graduate school. However, when controlling for professional experience the difference is not statistically significant.

If institutional prestige matters at all, it appears to matter most early in a scientist's career. When we examine the data by cohorts we find that graduate school prestige is a significant determinant of the prestige of a respondent's subsequent academic appointment during the first years of a scientist's career. Beyond five years, graduate school prestige is no longer significant. The cohort model thus supports Finkelstein's [14] contention that graduate school prestige matters most during the first years of an academic career. Whether or not a respondent is an early entrant, is of no consequence in explaining the prestige of his or her current university.

Thus, the neural network community does not provide evidence to support the 'backwater' hypothesis. Instead, we find that early entrants who persisted in neural network come from laboratories at the more prestigious graduate schools. None the less, what is interesting is that early entrants are more likely to be students as opposed to scientists who already hold their doctorate [40]. Although, as alluded to, we have to caution for the time-dependent nature of the data we collected. More specifically, graduates who entered early may be slightly underrepresented in the sample (thus introducing skewness) simply because they have retired at the moment of the survey.

We also have to point to two important limitations of the present study. First of all, as already mentioned, the data are based on a survey of one specific research community. In order to generalize from the findings discussed in this paper, it is necessary to compare graduates of more and less prestigious universities irrespective of research field. This clearly is an imperative for future research on the subject. Second, due to the nature of the citation impact scores, the present analysis is limited to the US academic context. It would, of course, be interesting to extend the study beyond US boundaries. Though, to do so, one will first have to examine and validate the reliability of the ISI impact ratings for foreign universities. This obviously is a research project in and of itself.

Finally, the comparison of early versus late entrants has raised the important issue of problem choice in R&D. Our previous research [11,39] has dealt with these issues in great detail. Both cognitive and social influences are prominent whenever a researcher decides to pursue a particular research agenda. For example, the intellectual appeal of the subject area, the availability of fellowships, the advice and guidance of one's supervisor all enter into the equation. It is not surprising that the comparison of 'early' versus 'late' entrants in terms of problem choice stimuli revealed interesting differences [11,39]. However, what is particularly striking in the context of this paper, is the lack of evidence to support the 'backwater' hypothesis in the field of inquiry studied. This finding, combined with the insights gained from the detailed analysis of problem choice behavior, suggests that perhaps the most important question for future research is to examine the influence of the length and the diversity of a scientist's professional experience (rather than institutional prestige or age) on pioneering behavior. This obviously is a challenging task.

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