# The Effect of University Affiliation on the Productivity of Scientists

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**Abstract:**

While knowledge production is central to economic growth, little is known on how universities contribute to the productivity of their faculty. Answering this question is difficult because scientists are not randomly allocated to universities; rather, top-tier universities hire the more talented scientists. In this paper we employ a method to correct for this bias and show that regardless of the scientists' talent upon PhD completion, the nurturing effect of the university tier-level is responsible for at-least 30% of the productivity of scientists. Our results provide evidence on the importance of institutions on academic productivity, implying that initial placements to universities have a significant role in scholarly performance.

**JEL Classification:**

**Keywords:**

Top tier universities like Harvard, MIT, and Stanford are leading the list of universities that scientists want to work for because of their high-quality research environment. Considering the relatively large supply of PhD candidates compared to number of faculty openings in these schools, one expects that the most talented individuals end up being hired by these top-tier universities. It is therefore not surprising that faculty in these universities are known to produce more quality research than faculty in lower ranked universities, and are typically believed to be more talented than their peers in lower tier universities. However, this belief of accurate matching between talent and university tier-level should not be taken lightly as it has major economic consequences. Faculty of top-tier universities are able to solicit larger amounts of funds to support research, and are provided privileges such as extra research support and reduced teaching loads, which are not equally available for faculty in lower ranked universities. They are further armed with learning opportunities, purpose and pride not equally present in other universities. This brings about the chicken and egg dilemma: To what extent can the relatively high productivity of researchers in top-tier universities be attributed to the researchers’ talent rather than the superior research environment of their universities?

Our objective in this paper is to infer how much of a researcher’s productivity can be attributed to talent (defined as research abilities at PhD completion)[[2]](#footnote-2) and how much can be attributed to the nurturing of the university that employed the researcher. Namely, there are two non-exclusive perspectives concerning the determinants of research productivity, whose relative contribution we aim to quantify. The *talent perspective* is that research abilities are predominantly determined by the time a researcher completed his/her PhD studies, and thus, scholarly productivity is not related to the identity of the university which hired the researcher upon PhD completion. Perhaps the most famous example supporting this notion is that of Nobel laureate Albert Einstein, who made extraordinary academic contributions during his initial career, even though he was not affiliated with a top-tier university.[[3]](#footnote-3) On the other hand, one must agree that research productivity of scholars at top-tier universities is achieved in an uneven playing field, under a highly supporting research environment. This observation supports the *nurturing perspective*, which claims that scholarly productivity is determined by the environment in which the researcher conducts research. According to this perspective, many scholars in lower ranked universities would have reached similar scholarly achievements as those of researchers in top-tier universities, if granted a similar, top-tier, nurturing environment. If the nurture component is significant it would imply that initial placement decisions have a significant role in scholarly performance. A role which is much more significant than commonly perceived. Accordingly, in this research we ask what is the relative role of university nurturing (vs talent), in research productivity.

Our empirical analysis concerns analyzing the research productivity of faculty over their academic career. In particular, we analyze finance[[4]](#footnote-4) researchers whose first affiliation is in one of the top-tier universities (defined as the top 20 ranked universities) and compare it against that of finance researchers whose first affiliation is in a second-tier university (universities ranked 51-100th).

Initial placement of researchers by hiring universities is not random; the more talented researchers are expected to more often be hired by top-tier universities than by second-tier universities. However, despite the effort invested in top-tier universities to find and hire the most talented individuals, misplacements may occur because talent is unobservable, and at PhD completion, the amount of information that exists to assess an individual’s talent is limited. We estimate the prevalence of errors in academic placement by analyzing the rate to which researchers' first academic employer is not consistent with their unobservable talent, which we proxy for by their ex-post initial productivity. To measure ex-post initial productivity, we quantify the researchers' scholarly productivity during the first five years of employment.[[5]](#footnote-5) We analyze two types of errors, the probability that highly talented individuals are initially hired by second-tier universities, and the probability that less talented individuals are hired by the top-tier universities. Our data shows that at least 28%-31% of the researchers that were hired by second tier universities exhibit productivity that warrants a top-tier placement, and that about 20-24% of the researchers in top-tier exhibit productivity that warrants a lower-tier placement. In striking contrast to these findings, we find that the job-market for academics is rigid. There are almost no cases of an upward employment move (from second-tier to top-tier), and 80% of researchers are employed at the same university tier-level (top-tier or second-tier) 10 years after their initial placement. Thus, though the data shows that the matching between an individual’s talent and the employing university’s ranking is imperfect, it seems that the job market for seasoned researchers does not correct for such misplacements.

Next, in order to study the magnitude of the nurturing component on productivity, we analyze the effect of the initial placement decision on the productivity of researchers in the long-term. We match authors across the two tier-groups based on their talent (i.e. accumulated research productivity within 5 years) and compare their productivity in the latter years (i.e. accumulated productivity in the consecutive years). Regardless of whether the individual was talented or not, we show that productivity is higher in the latter part of the career if the initial placement was at a top-tier university. Finally, we conduct cross sectional regression analysis to estimate the component of nurturing on productivity. We find that at least 30% of the productivity of researchers can be attributed to the nurturing quality of the university. These results support the notion that initial placement decisions, even if wrongly made, are a significant factor influencing the productivity of individuals in academia in later years.

The main contribution of the paper is in providing direct evidence for the marginal impact of university tier-level on the productivity of scientists. The labor economics literature has shown that observationally similar workers earn higher wages in larger firms than in smaller ones (e.g., Brown and Medoff, 1989; Evans and Leighton, 1989; Idson and Feaster, 1990), implying that employers have a first-order effect on productivity and wage. Similarly, recent evidence suggests that institutions have a first-order effect on knowledge creation (Furman and Stern, 2011). The current paper advances this literature by providing evidence that the tier-level of the hiring institution is a major determinant of research productivity even within a sample of already talented individuals.

A second contribution is to the literature on luck. A host of studies provide evidence that hiring decisions may be biased by factors unrelated to workers’ quality.[[6]](#footnote-6) Consequently, the idea that individuals’ luck determines the careers and financial well-being of individuals is often discussed in the academic and popular literature (Taleb, 2005; Mauboussin, 2012; Frank, 2016; Pluchino et al, 2018). The current paper quantifies the magnitude of misplacements in the finance academic profession at around 30%, implying that luck plays a non-trivial role also in the career of scientists.

Third, the paper contributes to the “nature versus nurture” question in human behavior and achievements. The relative importance of biology versus up-bringing is a prominent research area at the roots of scientific inquiry, dating back to the works of Darwin (1859) and Freud (1930). It is increasingly realized that almost any trait of human behavior is driven by some combination of nature and nurture.[[7]](#footnote-7) The current paper shows that nurturing, which can also be viewed as “on the job training” (e.g., Lynch, 1991; Black and Lynch, 1996; Konings and Vanormelingen, 2015), has important implications, even within a group of already talented individuals, such as scientists. Our lower bound estimate of a 30% nurturing component of a high-tier university compared to a lower-tier one, is remarkably high given that we consider the nurturing at later stages of life (post PhD), while estimates in the nature versus nurture literature consider nurturing as anything that happens after birth (Dickens and Flynn, 2001; Bowles and Gintis, 2002; Sacerdote, 2002; Barnea et al., 2010).

Finally, the paper provides a plausible explanation for the high skewness in productivity in academia, where few individuals publish most of the work (Price, 1986). The phenomenon has been noted to be one of the most perplexing problems in the sociology of science (Gaston,1978). Alison and Stewart (1974) claim that talent differences cannot explain the high variation in productivity, especially given that IQ correlates very weakly with productivity (Cole and Cole, 1973; Fox, 1983). Our findings that the nurturing of top-tier compared to second-tier is responsible for much of the productivity difference of researchers across the tiers, implies that some of the productivity-skewness phenomenon may be attributed to the skewness in the distribution of researchers’ initial affiliation: only few researches are nurtured by top tier schools, which we find is a core facilitator of productivity.

The rest of this paper is organized as follows. Section 2 describes the assembly of the data. Section 3 analyzes the errors in initial placement allocation of researchers to universities. Section 4 analyzes the talent and nurture components, and Section 5 concludes.

**2. Data**

Our data comes from the Thomson Reuters' Web of Science (WOS), from which we harvest our sample of authors, their affiliation, and list of publications. We study finance researchers, which are identified by having the majority of their articles published in Business Finance journals, according to the WOS classification (a total of 96 journals as of 2016). Since the WOS includes detailed data about affiliation only from 1966, our sample includes authors whose first publication on WOS appears no earlier than 1966. In addition, in order to observe the productivity of all the authors of our sample in the 10 years that follow their first publication, we do not include authors who had their first article published after 2006. We also create a second sample, in which we follow authors 20 years after their first publication, which means that in this sample we similarly drop authors whose first publication is after 1996. The appendix includes information on our sample generation process. We manually verified that our sample is complete and is consistent with 20 CVs of finance faculty that we have downloaded from personal faculty websites.

Overall, we were able to generate a sample of 3,707 authors, for whom we could generate an affiliation and publication trajectory over 10 years following their first publication. Our focus in this study is in comparing authors whose first placement is in a top 20 university (hence, top-tier) to those whose first placement is in universities ranked 51-100 (hence, second-tier).[[8]](#footnote-8) These two groups enable us to compare the nurturing difference between two types of research-oriented universities (as all universities which are ranked in the top 100 can be considered as such), that are sufficiently different in terms of their research quality reputation. Consequently, this comparison also allows us to estimate the extent to which an individual’s productivity pattern is affected by the tier-level of the university the individual is initially hired by.

Keeping only authors affiliated with one of these two tiers of universities, our sample consists of a balanced panel panel of 1572 authors whom we follow over 10 years (henceforth, Sample 1), and a balanced panel of 854 authors that we are able to follow over 20 years (henceforth, Sample 2).[[9]](#footnote-9) Accumulated productivity of an author is measured by the number of A publications (18 journals, listed in Step 3 of the appendix[[10]](#footnote-10)). The number of A publications provides is arguably the most objective productivity measure for quality research, as it is usually considered the most important productivity measure in tenure decisions, and because the importance of an A publication has been rather consistent over time (Fox, 1983; Gomez-Mejia and Balkin, 1992). Other measures, such as impact factor (of the journal) or citation count of an article, are noisier and hard to compare by because they have greatly changed over time and across finance disciplines.

**3. Analysis of authors' initial affiliation and research productivity**

**3.1 Affiliation of authors over tenure**

We first provide information about authors’ affiliation over time, which is provided in Table 1. We start with Sample 1. The sample includes 921 authors whose first affiliation is a top-tier university, and 651 authors whose first affiliation is a second-tier university. The most important takeaway from Sample 1 in Table 1 is that the authors’ affiliation is sticky. For example, 88.4% of the authors, whose first affiliation is in top-tier university, continue to be affiliated with a top-tier university in the following five years; and 89.2% of the authors whose first affiliation is in a second-tier university, continue to be affiliated with a university that is second-tier in the fifth year following their initial publication. The percentage of authors who move across affiliation tier-levels seems rather small, about 10% of the authors in both groups. We can also analyze the probability that authors in the sample have stopped producing research within 5 years of their initial publication. 7.2% of the authors stop conducting research within five years when the first affiliation is top-tier, while the figure is 12% when the first affiliation is second-tier.

One explanation for the relatively small change in the placement of authors by the five-year mark, is the tenure clock, which is commonly practiced in research universities. The average tenure clock is 5-7 years in most universities, and that could potentially lead, or force, authors to change their affiliation after, or just prior to, the tenure decision. Note though, that our tenure measure starts at first publication, so its correlation with tenure decision timing is probably not high. Nevertheless, to ensure that tenure decisions are not a major reason for this apparent immobility, we also provide the distribution of affiliation-tier changes by the 10-year mark. After 10 years, 78.7% (78.8%) of authors whose first affiliation is top-tier (second-tier), still appear as being affiliated within the same tier-level universities. Thus, there appears to be a rather high-level of stickiness in employment, in the sense that the ranking of the first affiliation is also the ranking of the affiliation after 10 years for approximately 80% of the sample. Important, the evidence of an upward move across affiliation tiers is almost nonexistent. Only 2.0% of the authors whose initial affiliation is second-tier move to a top-tier university within 5 years, and that percentage increases by a mere 0.3% (to 2.3%) by the 10-year mark.

We repeat the analysis for Sample 2, which allows us to follow authors over a 20-year period. Though the sample is smaller and the publication are, on average, of authors with more years of experience, the evidence of the relative immobility persists in this sample. About 75% of the authors are affiliated with a school of the same ranking as the initial ranking institution, though there is a larger percentage of authors that seem to have made a move to a top-tier university after 20 years (4.1% by 20 years of activity compared to 2.0% by 10 years). Overall, the evidence is broadly consistent with the idea that the academic market is segmented. Authors tend to be affiliated with the same tier-level institutions in 70-80% of cases, and an upward move from a second-tier university to a top-tier university is extremely rare.

**3.2 Author's first affiliation and research productivity over time**

We next analyze the heterogeneity in author's productivity depending on whether the author's first employer is a top-tier or second-tier university. The top and bottom plots of Figure 1 provide the accumulated number of A articles for Sample 1 and Sample 2, respectively. For each tenure year we provide the mean, the top quartile, and top 10% of the number of accumulated A articles depending on first employer tier level. It is evident from the figure that the authors whose first placement is in a top-tier university are on average more productive than their peers whose first placement is in a second-tier university. For example, for sample 2, the top 10% of authors in a top-tier university have 12 or more A accumulated publications at year 20, while the corresponding number for authors whose first affiliation is second-tier is only 5 or more A publications. Nevertheless, the figure shows that there is an obvious high level of heterogeneity in authors' productivity within a tier-level. For example, we can see that the top 10% percentile of authors whose first placement is in a second-tier university is clearly above the mean productivity of authors whose first placement is in a top-tier university; also, the top 10% percentile of authors whose first placement is in a second-tier university follows a similar trajectory to that of the top 25% percentile of authors whose first placement is top-tier. In fact, for sample 2, the two trajectories are overlapping up until year 7. Similarly, the top quartile of authors whose first placement is second-tier, seem to track, up till year 5-7, the mean trajectory of authors whose first placement is top-tier. This implies two things. First, there is large heterogeneity in productivity within a first placement tier. If one takes the view that productive authors strive to move to top-tier universities, this heterogeneity seems to be inconsistent with the relative low level of author-mobility that we observed in Table 1. Second, over-time the difference in productivity, as related to first placement tier-level, seems to grow.

We next provide more detailed information on the heterogeneity in productivity depending on the first affiliation tier-level of the author. Figure 2 (and Table 2) provide the distribution of authors according to their productivity in terms of the number of A level published articles. The top diagram of Figure 2, which concerns Sample 1, provides the accumulated productivity at year 5; while the bottom diagram, which concerns Sample 2, provides the accumulated productivity at year 10. There are several insights that can be taken from Figure 2 and Table 2 that are worth noting. First, there is a positive relation between accumulated productivity and the first affiliation tier-level of the author. For example, for Sample 1, we observe that 24.6% of the authors whose first affiliation is a top-tier university, have no A articles after 5 years; while that percentage is about double (48.2%) for second-tier university. Second, the percentage of authors that have a single A publication is similar in both tier-levels. Third, if an author has two A articles or more, it is more likely that the author's first affiliation is with a top tier institution. Also, the percentage of authors having more than 4 A articles after 5 years is very low. Only 9.8% of the authors whose first affiliation is top-tier, and 2% of the authors whose first affiliation is second-tier, have an accumulated productivity of more than 4 A articles. Finally, the distribution in productivity after 10 years looks similar to that of 5 years. The only major difference is that it is more skewed to the right after 10 years compared to 5 years, which is expected given that differences in productivity should become more apparent over time. Overall, the evidence of Table 2 shows that authors’ first affiliation is strongly related to their productivity, but there is much heterogeneity in authors' productivity within a tier level, as well as considerable overlap across tiers.

**3.2 Errors in first placement decisions**

Our next step is to better understand the academic job market efficiency, in terms of placing researchers in the most fitting institutions. Naturally, given the better career advancement potential in top universities, researchers would typically strive for employment by these institutions. Therefore, it is conceivable that the matching of PhD graduates to universities is mostly demand driven; i.e. the top-tier universities employ the researchers which they perceive to be those that have the highest potential in research productivity, and the second-tier school researchers are hired from candidates that were not picked by the top-tier schools. Obviously, hiring institutions cannot fully predict the productivity of an individual, so some researchers may not be hired by top universities even though they eventually turn out to be highly productive (which we define as a type 1 error); and some researchers may be hired by a top-tier university even though they end up showing low productivity levels (which we define as a type 2 error). In this section, we analyze the prevalence of both types of errors.

Table 3 provides our quantification of misplaced authors based on their accumulated productivity after 5 years (Panel A) and 10 years (Panel B). We start by quantifying the percentage of researchers whose first affiliation is a second-tier university, although their realized productivity after 5 years warrants a first-tier placement. Because there is a total of 1572 authors in Sample 1, from which 921 authors have their first affiliation in a top-tier university, perfect placement efficiency would mean that the 921 most productive authors are hired by a top-tier university employer.[[11]](#footnote-11) In the table, column (1) lists the accumulated number of authors whose productivity is at least (i.e. greater than or equal to) the number shown in column (0). For example, data about the number of authors with at least 3 A publications (i.e., the row that has 3 in column 0), shows us that there are 369 authors in Sample 1 (column 1 of that row) with such accomplishments by the end of their 5th year mark. When looking for a productivity level of the 921 most productive researchers, we find (from column 1) that the closest (but still smaller) number compared to 921 is 654, which corresponds to a productivity of at least 2 A articles. Thus, we can conclude that under an efficient placement market, authors who ended up publishing 2 A articles or more within 5 years, should have been affiliated with a top-tier university. Column (2) provides the number of authors whose first affiliation is in second-tier university, and who achieve a higher or equal productivity than the number of articles that appears in column (0). For example, 14 authors published 5 or more A articles, and that amounts to 13.5% of the 118 authors in the sample that have such a productivity record (14 second tier authors and 104 first tier authors), or about 1 in 7.5 authors. Using this information, we see that 182 authors whose first affiliation is a second-tier university were successful in reaching the estimated top tier benchmark, of 2 or more A articles. This corresponds to 27.8% of the second-tier affiliated authors of the sample (i.e., approximately 1 in every 3 authors). Note, however, that this calculation does not consider the number of top-tier and second-tier affiliates. For example, if the sample included a much larger number of second-tier authors compared to top-tier, then having 27.8% of the high-quality authors in second-tier may not seem like a big mistake. Therefore, to better assess the prevalence of misplacement, type 1 error is defined as the number of authors whose first placement warrants a first-tier affiliation as a percentage of the total number of authors whose first affiliation is second-tier. This results in an estimate of 28% (but note that this is a lower bound estimate, given the discreetness of the distribution of the accumulated number of publications).

We next move to quantify type 2 errors. Type 2 errors occur when an author’s first affiliation is a top-tier university, while the author’s realized productivity warrants a second-tier placement. In Sample 1 we have 651 second-tier authors, so a perfect matching of first placement according to future productivity would have the 651 least productive researchers hired by second-tier universities. In column (4) we have the accumulated number of authors, whose publication record of A articles after five years is, at most, the number of publications indicated in column (0); and in column (5) we have the accumulated number of authors with such accomplishments whose first placement is a top-tier school. Note that the closest number to 651 that does not exceed it in column (4) is 541, which corresponds to a productivity level of 0 A articles by the 5-year mark. Hence, only authors with no A articles can be considered misplaced if their first affiliation is a top-tier schools. Thus, type 2 error, which is defined as the percentage of top-tier authors whose productivity warrants a second-tier placement is 24.6%. Hence, we conclude that 1 in 4 authors whose first affiliation is in a top-tier university is misplaced (again, note that this is a lower bound estimate).

Finally, we repeat the analysis for Sample 2, where misplacement is measured at year 10. Interestingly, the results remain relatively unchanged. Based on Panel B, one can conclude that 31.7% of the authors whose first placement is second-tier have a productivity level that warrants a top-tier affiliation; and about 20% of authors whose first placement is first-tier have a productivity level that warrants a second-tier affiliation.

**4. Assessing the effect of the first affiliation**

Our premise is that the top-tier universities provide a superior nurturing environment for conducting research than second-tier universities do. Namely, researchers working in top-tier universities are exposed to better research practices, are able to cooperate with leading researchers, have more access to funding, and are encouraged to achieve research excellence compared to researchers affiliated with second-tier universities.

The degree of performance heterogeneity that we have observed within and across the two-tiers allows us to study the relative importance of talent and nurturing on research productivity. Our analysis in this respect is inspired by the literature that analyzes nature versus nurture by comparing identical twins. In that line of research, since identical twins have the same DNA, exposing them to different nurturing environments enables one to assess the effect of the environment on different outcomes. In our analysis, however, we do not observe pairs of researchers with identical talent (same research ability when finishing the PhD degree); however, we can match individuals based on their research productivity at year 5. Assuming that there is only a limited degree of nurturing in the first 5 years as faculty, researchers with the same accumulated productivity at the 5 year mark can be regarded as having similar talent, no matter whether they landed a job in a top-tier or second-tier university.[[12]](#footnote-12) This means, that if we follow the two individuals’ productivity during the years after the matching year (from tenure=6), we should be able to learn whether the expected better nurturing in top-tier universities is important. If the accumulated productivity of the second-tier author is no less than that of the top-tier author, we can conclude that talent is the sole determinant of research productivity. That is, regardless of where the researcher lands his/her first position, the talent of the individual ultimately determines research productivity. However, if the accumulated productivity of the second-tier author becomes lower than that of the top-tier author, we can reject the null that nurturing has no effect in shaping the research trajectory of the researcher. Given the relatively high level of misplacement we observe (Table 3), such a conclusion would imply that luck in first placement has a major effect on the productivity of academics throughout their career.

**4.1 Matching of research based on accumulated productivity**

Table 4 and Figure 3 summarize our analysis of the mean accumulated productivity of authors between the end of the year 5 mark and the year 10 mark. For each author in Sample 1, we count the accumulated number of A articles published by the end of year 5 (our measure of talent). We then partition authors to groups according to the tier level of their first affiliation and according to their talent. Table 4 provides difference of means test in accumulated productivity in years 6-10, between top-tier and second-tier authors that had same observed talent at year 5. In this analysis we follow 90% of the authors, namely, those that had between zero and four A articles by year 5.[[13]](#footnote-13) The takeaway from Table 4 is that authors with the same productivity level early in their career, become different due to first-placement affiliation. By year 10, the researchers with an initial affiliation of a top tier university become more productive than the researchers affiliated with a lower tier university. By year 8, the difference in accumulated A articles between top-tier and second-tier affiliated authors is significant across all initial talent levels. As one may expect, the average difference in accumulated productivity is larger in magnitude for the more talented authors, i.e. those who have a higher initial productivity.

Figure 3 provides the same information as Table 4, but rather than the total accumulated productivity at year 6-10, it includes the accumulated productivity of authors starting at year 6 (therefore all plots start from the origin). The black-lined plots are of authors whose first placement is a top-tier university, while the red-lined plots are of authors whose first placement is a second-tier university. Plots that have the same composition (solid, dash, etc.) correspond to authors of similar talent, i.e., accumulated productivity at end of year 5. There are few takeaways that are easier to see in the figure than in the table. First, one can clearly observe that the black-lined plots are above the red-lined plots for all initial talent levels. Second, the slope of plots within a tier level (within a plot color) is higher, the higher was the initial talent. Hence, authors’ productivity is persistently related to talent. Third, the trajectory of the average accumulated productivity of zero A articles of authors whose first placement is top-tier is similar to that of authors with one A article, and whose first placement is second-tier. Fourth, the most talented authors in second-tier universities (the 3 A and 4 A red-line plots), have a similar trajectory to that of authors whose first placement is a top-tier school but have only medium talent (2 A articles by year 5). Overall, the evidence is consistent with the notion that the first placement decision makes a difference, after controlling for the talent of individuals. Hence, we interpret the results as evidence that institutional nurturing is a major contributor to the research productivity of researchers.

**4.2 Quantifying the talent and nurture component in productivity**

We next analyze the extent to which a researcher's productivity can be attributed to the better nurturing environment that exists in top-tier universities. For this, we analyze research productivity in the years 6-10 (Sample 1) and years 6-20 (Sample 2) as a function of the talent and nurture component of the individual. Namely, we estimate the following regression specification,

(1)

where is an indicator that equals one if author *i* published at least one A article during tenure year *t* (, and zero otherwise, *Talent* is the number of A articles accumulated by author *i* till year 5; *Nurture* equals one if the author's *i* first affiliation (at t=1) is a top-tier university, and zero if it is a second-tier university. Logistic regression is used to estimate eq. (1).

Table 5 provides the results pertaining to the estimation of eq. (1). In specifications (1)-(3) the coefficients provide the marginal effects at the mean of the sample. As expected, both talent and nurture are significant predictors of a researcher's productivity. According to specification (1), an increase in one unit of talent (an increase in one A article by year 5) increases the probability of publishing in a given year (in years 6-10) by 4.5%. According to specification (2), affiliation to a top-tier university compared to a second-tier increases the probability of publishing in a given year (in years 6-10) by 10.5%. Specification (3) estimates the talent and nurture effects jointly. Note that the 4.1% in specification (3) is not much different than the 4.5% estimate in specification (1), which is consistent with the idea that initial productivity proxies well for talent, as it provides a relatively constant measure of a researcher's ability, irrespective of the institution that employed the researcher. Differently, the nurture component of 5.6% in specification (3) is about half of the 10.5% estimate in specification (2), which is not surprising because individuals are not randomly allocated (i.e. hired) to institutions, i.e., in the stand-alone specification (2), the nurture coefficient captures the effect that higher talent individuals tend to be hired by top-tier universities. In essence, by comparing specification (3) and (2), one can conclude that half of the university-affiliation effect estimated in specification (2) can be attributed to the selection bias, and half to nurturing.

Specification (3) does not permit the assessment of the relative importance of talent versus nurture because the coefficients' magnitudes depend on the scale of the independent variables. In our model, talent is a discrete variable that takes on values between 0-9, while nurture is an indicator variable. Comparing the coefficient without considering their variation is not appropriate. In OLS regressions, standardized regression coefficients are usually used in order to compare coefficients (e.g., Kim and Ferree, 1981:24-25). While there is still some subjective component in interpreting the magnitude of a standardized effect (for example, some researches prefer the interquartile range), this approach does provide a framework for comparison and is commonly used in the finance and economics literature (see for example, Rubin and Smith, 2011). Since our case involves a logit estimation, we cannot standardize the dependent variable. However, Kaufman (1996) shows that quantifying the relative importance of variables in a logit regression can be achieved by first standardizing the independent variables and then comparing their magnitude. Applying this method, we provide the results in specifications (4) and (5). We find that the coefficient of nurture is 0.245, and that of talent is 0.607, implying that 29% of the (talent plus nurture) productivity variation can be attributed to nurture (i.e., 0.245/(0.245+0.607)). Specification (5) repeats specification (4) with two additional variables: an interaction term and tenure. The interaction term is negative, suggesting that individuals with high talent are less affected by the nurturing environment. The tenure effect is insignificant. The bottom part of the table repeats the analysis for Sample 2. The results are rather similar, both in magnitude and significance. The only noticeable difference is in the effect of tenure, which becomes negative as tenure increases. It seems that in years 10-20 researchers are on average less productive compared to years 6-10. Important, according to specification (9) and (10), the lower bound on the nurture component is very similar to the lower bound estimated in Sample 1, and ranges at 30-32%.

**Conclusions**

In this research we analyze the impact that an institution’s tier-level has on the productivity of scholars, while addressing the selection-bias problem that the top-tier institutions tend the hire the more talented individuals.

We find that while on average top institutions employ more talented researchers there is a substantial heterogeneity in productivity within each university tier level, implying that about 30% of researchers can be considered as having a productivity level that is unfitting to their tier-level placement. Further, while productive researchers may be missed by top universities, our analysis shows that upward mobility is very limited and it is unlikely that productive researchers would be able to eventually be hired by the top-tier universities. Consequently, our analysis shows that having a "lucky-break" and getting hired by a top-tier university is important in facilitating a productive research career. Reasons behind the rigidness of the seasoned market for researchers may be suggested. One possibility is that there is a time-lag between nurturing and productivity. That is, it is possible that only after a few years of nurturing productivity emerges. This means that missing the important nurturing effect of a top-tier school as a first employer is very difficult to overcome. A second possibility is that faculty at top tier universities are limited in their openness to the possibility of hiring a talented seasoned researcher from a lower-tier university. For example, such a hire may overshadow incumbent scholars, and furthermore, the probability of cooperating with a seasoned scholar is reduced (as such scholars typically have an established research trajectory with other authors).

Regardless of the reasons for the placement rigidness, we find that first placement affiliation has a major consequence on one’s career. Our estimates show that approximately 30% of the productivity of a researcher can be attributed to the nurturing of the first hiring institution. Further, regardless of the researcher’s talent, a researcher’s scholarly productivity is higher at a top-tier compared to a second-tier university. These apparent superior nurturing effects in top institutions can be either related to learning, guidance and cooperation with top researchers, or the emphasis placed on research and incentives. For example, the stronger emphasis placed on research as compared to teaching in top-tier universities, compared to second-tier schools could be detrimental for the research career at lower-tier universities. Interestingly, it is common to ignore the variation in nurturing across universities and assess the scholarly activity of a researcher independently of his/her initial placement.[[14]](#footnote-14) Perhaps this practice should be re-considered. Overall, the findings of the paper shed light on institution having a major influence in research productivity.

**Appendix:**

The sample of authors and their productivity is generated by harvesting data from the WOS and processing it to generate uniquely identifiable author names, associated affiliations, and ranks. The algorithm consists of four steps, to eventually create a panel of the authors' productivity over the years.

**Step 1: Author names**: All articles which are authored by at least one researcher that is affiliated with a business school, a management department, a school of commerce, or a finance area/department are extracted from the WOS. For each author of any of the extracted articles, the entire list of his/her published articles on the WOS is extracted. We then keep only authors (and their corresponding list of articles) whose majority of articles are published in journals that meet one of the following criteria: The journal is classified as Business Finance by the WOS; the journal is one of the top five general-interest economics journals; the journal is one of the top six general-interest accounting journals (henceforth, finance related articles). These criteria help ensure that the sample we generate is of finance researchers, and also that all the authors in our sample are uniquely identified by name. For example, suppose that Smith, D. is a common name. If there are two Smith, D. finance researchers in our sample, this means that the name is relatively a common name, and therefore would also probably be a common name of authors in other management fields (recall that all publications associated with a management affiliation are considered). Because finance constitutes for about between 1/3 and 1/4 of articles made in business related fields, the criterion of at least 50% finance related articles for an author would not hold, so the algorithm will drop Smith, D. from the sample of authors. Thus, we overcome the author ambiguity problem by dropping authors that have common names. Out of 18,153 authors who publish in Business Finance, we end up with 12,581 unique authors following this step.

**Step 2: Linking affiliation to author:** We next need to identify the affiliation of the authors. In many cases, the affiliation of authors is clearly provided by the WOS. If this is not the case, the WOS provides a separate author list and affiliation list, and typically (but not always) an author’s affiliation would correspond to the same ordinal position of the author in the reference list. However, occasionally the number of authors and number of affiliations do not match, for example, it can happen in earlier years if two authors are from the same affiliation. We therefore programed an algorithm to assign authors with their affiliation. First, if the paper is a sole-authored paper, we mark the affiliations as that of the sole author. Similarly, if the number of affiliations corresponds to the number of authors, we match the ordinal order of the author with that of the affiliation. In other cases, we choose the affiliation of the authors among those that appear in the articles, if and only if the affiliation appears in other articles of the author during the year, for which the matching to affiliation is clear. If that is not sufficient, we chose the affiliation which appears on the article and also is the most common affiliation of the author during the three years centered at the article's publication year. If there is no other article during the three years centered at the article’s publication year, the coauthors of the paper may have an affiliation, which may result in only one affiliation that is not assigned to any other author, and thus assigned to the author in question. If we still do not have a match, we fill the gap by keeping the previous confirmed affiliation for the author (i.e. from a previous year) or the following confirmed affiliation (i.e. from a consecutive year), if it is a listed possibility on the article. When an author has more than one affiliation in an article, we keep the affiliation which is the most common during the year. We drop authors who do not have at least one article that is uniquely associated with an affiliation.

We define an author's year zero in our study as the first year in which an article of the author is published on the WOS. For an author to be included in the sample, the first article and last article must be published on different years, which implies that we drop all authors who have only one publication on the WOS or appear on the WOS for less than two years. Overall, these affiliation identification criteria yield a sample of 6,289 authors. Most of the authors that are dropped during this step are those that have only one publication on the WOS.

**Step 3: Ranking institutions:** We rank institutions based on the number of A finance related publications that the authors in our sample have throughout the sample years 1966-2016. The ranking is based on the authors in our sample, to eliminate the possibility that certain institutions are misrepresented in our sample due to the first two steps of the algorithm (for example, if Xu and Chen are very common names in China, our ample may under-represent Chinese universities). The larger the number of A publications the higher the ranking of the institution. There are 18 A journals in our analysis, which include all highly ranked journals in finance related fields. These include the top six finance journal (Journal of Business, Journal of Finance, Journal of Financial and Quantitative Analysis, Journal of Financial Economics, Review of Financial Studies, and Review of Finance, the top six accounting journals (Accounting Review, Journal of Accounting & Economics, Journal of Accounting Research, Review of Accounting Studies, Cotemporary Accounting Research, and Accounting Organizations and Society), the top 5 economics journals (American Economic Review, Econometrica, Journal of Political Economy, Quarterly Journal of Economic, Review of Economics Studies), as well as Management Science.

**Step 4: Accumulating productivity**: Our productivity variable is the number of A publications that author has authored since initial article's year zero on WOS. By definition, if an author does not appear after a certain year, e.g., year 5, his accumulated A publications record will not change from that point onwards (in year 6-10). However, to avoid a possible survival bias, we keep such authors in our panel. In other words, the panel of authors we analyze is balanced and all authors would have the same number of yearly observations. However, the results are not materially different when working with an unequal panel. Overall, we end up with a sample of 6,289 authors, of which 3,707 first appear on the WOS prior to 2007.

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Figure 1: Number of articles based on first placement:

Authors are partitioned into two tier groups based on their first placement. The y-axis is the number of publications and the x-axis is the tenure year. The various plots depict the group's mean, top 25% percentile, and top 10% percentile publication level over the authors tenure year (since first publication on WOS).

Figure 2: Accumulated productivity distribution

The figure provides the distribution of authors based on the number of A articles published in their first 5 years (for Sample 1) and first 10 years (for Sample 2).

Figure 3: Accumulated productivity starting at year 6

Authors are grouped based on their first affiliation and number of A articles they published during the first 5 years. The figure plots that mean number of accumulated A articles between end of year 5 and year 10.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 1: Affiliation of authors over time**  The table provides information on number of authors in each of the samples, as well as authors’ affiliation distribution after 5 and 10 years of tenure (for Sample 1), and 10 and 20 years of tenure (for Sample 2). | | | | | | | | |
|  | Sample 1 | | | | Sample 2 | | | |
| First affiliation | Top 20 universities | | Top 51-100 universities | | Top 20 universities | | Top 51-100 universities | |
| # of authors | 921 | | 651 | | 561 | | 293 | |
|  | Affiliation (% of authors) | | | | Affiliation (% of authors) | | | |
|  | after 5 years | after 10 years | after 5 years | after 10 years | after 10 years | after 20 years | after 10 years | after 20 years |
| University rank |  |  |  |  |  |  |  |  |
| Less than 100 | 4.5 | 8.3 | 6.6 | 15.5 | 4.6 | 10.3 | 7.8 | 14.0 |
| Top 51-100 | 2.9 | 5.3 | 89.2 | 78.8 | 4.5 | 6.4 | 86.7 | 76.1 |
| Top 21-50 | 4.2 | 7.7 | 2.2 | 3.4 | 7.7 | 10.2 | 3.4 | 5.8 |
| Top 20 | 88.4 | 78.7 | 2.0 | 2.3 | 83.2 | 73.1 | 2.0 | 4.1 |
|  | Authors with no articles published after tenure=5 | | | | Authors with no articles published after tenure=10 | | | |
|  | 7.2% | | 12.0% | | 16.9% | | 22.2% | |

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| --- | --- | --- | --- | --- | --- | --- |
| **Table 2: Authors’ first affiliation and number of A publications**  The table provides the distribution of authors productivity, measured by the number of A articles accumulated over the first 5 years (10 years) in Sample 1 (Sample 2), as well as the difference in means tests across the two tier levels. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. | | | | | | |
|  | Sample 1 | | | Sample 2 | | |
| Number of A articles | Top 20 universities  (% of authors) | Top 51-100 universities  (% of authors) | Difference | Top 20 universities  (% of authors) | Top 51-100 universities  (% of authors) | Difference |
| 10+ | 0.0 | 0.0 | 0.0 | 2.3 | 0.3 | 2.0\*\* |
| 9 | 0.3 | 0.0 | 0.3 | 2.3 | 0.0 | 2.3\*\*\* |
| 8 | 0.7 | 0.0 | 0.7\*\* | 2.0 | 0.3 | 1.6\* |
| 7 | 1.5 | 0.3 | 1.2\*\* | 3.9 | 0.0 | 3.9\*\*\* |
| 6 | 2.4 | 0.6 | 1.8\*\*\* | 3.4 | 1.0 | 2.4\*\* |
| 5 | 4.9 | 1.2 | 3.7\*\*\* | 8.2 | 2.4 | 5.8\*\*\* |
| 4 | 7.5 | 2.6 | 4.9\*\*\* | 8.7 | 5.8 | 2.9 |
| 3 | 14.4 | 7.1 | 7.4\*\*\* | 11.4 | 9.2 | 2.2 |
| 2 | 19.5 | 16.1 | 3.4\* | 16.9 | 12.6 | 4.3\* |
| 1 | 24.1 | 23.8 | 0.3 | 20.9 | 21.8 | -1.0 |
| 0 | 24.6 | 48.2 | -23.6\*\*\* | 20.0 | 46.4 | -26.5\*\*\* |
|  |  |  |  |  |  |  |
| Total number of authors | 921 | 651 |  | 561 | 293 |  |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 3: Misplaced authors in their first appointment**  The table provides the number and percentage of misplaced authors defined as productive authors whose first affiliation is the top 51-100 universities (type 1 error) and unproductive authors whose first affiliation is in the top 20 universities (type 2 error). Productive (unproductive) authors are based on the accumulated productivity of the authors at tenure=5 in Panel A, and at tenure=10 in Panel B. An author of a top 51-100 university is considered productive if his/her productivity is equal or above the accumulated productivity of the top 921 authors in Panel A (561 authors in Panel B), which corresponds to the number of top 20 authors in the respective sample. A top 20 university author is considered unproductive if his/her productivity is equal or below the accumulated productivity of the bottom 651 authors in Panel A (293 authors in Panel B), which corresponds to the number of top 51-100 authors in the respective sample. | | | | | | | |
| **Panel A: Productivity at tenure= 5 (Sample 1)** | | | | | | | |
| (0) | (1) | (2) | (3) | (4) | | (5) | (6) |
| Number of A articles | Accumulated number of authors having >= | Accumulated numbers of authors in top 51-100 universities >= | Misplaced authors (%)  (2)/(1) | Accumulated number of authors having <= | | Accumulated numbers of authors in top 20 universities <= | Misplaced authors (%)  (6)/(5) |
| 10+ | 0 | 0 | NA | 1572 | | 921 | -- |
| 9 | 3 | 0 | 0 | 1572 | | 921 | -- |
| 8 | 9 | 0 | 0 | 1569 | | 918 | -- |
| 7 | 25 | 2 | 8.0 | 1563 | | 912 | -- |
| 6 | 51 | 6 | 11.8 | 1547 | | 898 | -- |
| 5 | 104 | 14 | 13.5 | 1521 | | 876 | -- |
| 4 | 190 | 31 | 16.3 | 1468 | | 831 | -- |
| 3 | 369 | 77 | 20.9 | 1382 | | 762 | -- |
| 2 | **654** | **182** | 27.8 | 1203 | | 629 | -- |
| 1 | 1031 | 337 | -- | 918 | | 449 | -- |
| 0 | 1572 | 651 | -- | **541** | | **227** | 42.0 |
| Type 1 error | | 182/651=28% | | Type 2 error | 227/921=24.6% | | |
| **Panel B: Productivity at tenure = 10 (Sample 2)** | | | | | | | |
|  | (1) | (2) | (3) | (4) | | (5) | (6) |
| Number of A articles | Accumulated number of authors having >= | Accumulated numbers of authors in top 51-100 universities >= | Misplaced authors (%)  (2)/(1) | Accumulated number of authors having <= | | Accumulated numbers of authors in top 20 universities <= | Misplaced authors (%)  (6)/(5) |
| 10+ | 14 | 1 | 7.1 | 854 | | 561 | -- |
| 9 | 27 | 1 | 3.7 | 840 | | 548 | -- |
| 8 | 39 | 2 | 5.1 | 827 | | 535 | -- |
| 7 | 61 | 2 | 3.3 | 815 | | 524 | -- |
| 6 | 83 | 5 | 6.0 | 793 | | 502 | -- |
| 5 | 136 | 12 | 8.8 | 771 | | 483 | -- |
| 4 | 202 | 29 | 14.4 | 718 | | 437 | -- |
| 3 | 293 | 56 | 19.1 | 652 | | 388 | -- |
| 2 | **425** | **93** | 21.9 | 561 | | 324 | -- |
| 1 | 606 | 157 | -- | 429 | | 229 | -- |
| 0 | 854 | 293 | -- | **248** | | **112** | 45.2 |
| Type 1 error | | 93/293=31.7% | | Type 2 error | 112/561=20.0% | | |

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| --- | --- | --- | --- | --- | --- | --- |
| **Table 4: Accumulated productivity of matched authors**  The table provides the accumulated number of A articles of authors in tenure 6-10 (Sample 1). Authors whose first affiliation is in a top 20 university are matched to authors whose first placement is to a top 51-100 university based on their accumulated number of A publications at tenure=5. The mean accumulated number of A articles of each subgroups is tabulated as well as the difference between the two groups’ mean accumulation. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. | | | | | | |
| Tenure | 5 | 6 | 7 | 8 | 9 | 10 |
| **No A articles** |  |  |  |  |  |  |
| Top 20 | 0 | 0.12 | 0.19 | 0.29 | 0.4 | 0.51 |
| Top 51-100 | 0 | 0.02 | 0.05 | 0.08 | 0.11 | 0.14 |
| Difference | 0 | 0.10\*\*\* | 0.14\*\*\* | 0.21\*\*\* | 0.29\*\*\* | 0.37\*\*\* |
| **1 A article** |  |  |  |  |  |  |
| Top 20 | 1 | 1.13 | 1.33 | 1.5 | 1.63 | 1.76 |
| Top 51-100 | 1 | 1.15 | 1.26 | 1.33 | 1.41 | 1.5 |
| Difference | 0 | -0.02 | 0.07 | 0.17\*\* | 0.22\*\* | 0.26\*\* |
| **2 A articles** |  |  |  |  |  |  |
| Top 20 | 2 | 2.22 | 2.43 | 2.64 | 2.91 | 3.1 |
| Top 51-100 | 2 | 2.17 | 2.26 | 2.47 | 2.7 | 2.91 |
| Difference | 0 | 0.05\*\* | 0.17 | 0.17\* | 0.21\*\* | 0.19\*\*\* |
| **3 A articles** |  |  |  |  |  |  |
| Top 20 | 3 | 3.38 | 3.73 | 4.04 | 4.39 | 4.7 |
| Top 51-100 | 3 | 3.17 | 3.37 | 3.61 | 3.85 | 3.93 |
| Difference | 0 | 0.21\*\* | 0.36\*\* | 0.43\*\* | 0.54\*\* | 0.77\*\*\* |
| **4 A articles** |  |  |  |  |  |  |
| Top 20 | 4 | 4.61 | 4.97 | 5.45 | 5.77 | 6.25 |
| Top 51-100 | 4 | 4.29 | 4.47 | 4.65 | 4.88 | 5.35 |
| Difference | 0 | 0.32 | 0.50\* | 0.80\*\* | 0.89\*\* | 0.90\* |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 5: Productivity in later career as a function of talent and nurture**  The table provides logit regression results, where the dependent variable is one if the author had an A publication during the year, and 0 otherwise. Only author-year observations that come after tenure=5 are included in the estimation. Talent is the number of A publications accumulated by the author till tenure=5; Nurture equals one if the author's first affiliation (at tenure=1) is a top-tier university, and zero if it is a second-tier university. Tenure is the number of years elapsed since the author's first publication on WOS. In specification (1)-(3) and (6)-(8), marginal coefficient at the means are provided. In specification (4)-(5) and (9)-(10) all independent variables are standardized in order to compute the lower bound for the nurture effect out of the total nature + nurture effect, which is listed in the last row for each sample of results. All specifications include an intercept, t-statics are provided in parenthesis. \*, \*\*, and \*\*\* indicate significance at the 10%, 5%, and 1% level, respectively. | | | | | |
|  | **Productivity in tenure 6-10 (Sample 1)** | | | | |
|  |  |  |  | Standardized independent variable | |
|  | (1) | (2) | (3) | (4) | (5) |
| Talent | |  | | --- | | 0.045\*\*\* | | (22.57) | |  | |  | | --- | | 0.041\*\*\* | | (19.37) | | |  | | --- | | 0.607\*\*\* | | (20.20) | | |  | | --- | | 0.958\*\*\* | | (14.28) | |
| Nurture |  | |  | | --- | | 0.105\*\*\* | | (12.65) | | |  | | --- | | 0.056\*\*\* | | (6.58) | | |  | | --- | | 0.245\*\*\* | | (6.56) | | |  | | --- | | 0.485\*\*\* | | (8.55) | |
| Talent × Nurture |  |  |  |  | |  | | --- | | -0.443\*\*\* | | (-5.89) | |
| Tenure |  |  |  |  | |  | | --- | | -0.044 | | (-1.31) | |
| Pseudo R squared | 0.0805 | 0.0242 | 0.0872 | 0.0872 | 0.0929 |
| # obs | 7,860 | 7,860 | 7,860 | 7,860 | 7,860 |
| Lower bound for nurture effect; i.e., b[nurture]/(b[talent]+b[nurture]) | | | | **29%** | **34%** |
|  | **Productivity in tenure 6-10 (Sample 2)** | | | | |
|  |  |  |  | Standardized independent variable | |
|  | (6) | (7) | (8) | (9) | (10) |
| Talent | |  | | --- | | 0.033\*\*\* | | (25.57) | |  | |  | | --- | | 0.030\*\*\* | | (21.88) | | |  | | --- | | 0.546\*\*\* | | (22.37) | | |  | | --- | | 0.926\*\*\* | | (13.03) | |
| Nurture |  | |  | | --- | | 0.085\*\*\* | | (13.35) | | |  | | --- | | 0.046\*\*\* | | (7.10) | | |  | | --- | | 0.238\*\*\* | | (7.02) | | |  | | --- | | 0.434\*\*\* | | (8.59) | |
| Talent × Nurture |  |  |  |  | |  | | --- | | -0.435\*\*\* | | (-5.67) | |
| Tenure |  |  |  |  | |  | | --- | | -0.076\*\*\* | | (-2.66) | |
| Pseudo R squared | 0.0671 | 0.0198 | 0.0728 | 0.0728 | 0.077 |
| # obs | 12.810 | 12.810 | 12.810 | 12.810 | 12.810 |
| Lower bound for nurture effect; i.e., b[nurture]/(b[talent]+b[nurture]) | | | | **30%** | **32%** |

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2. In this paper "Talent" refers to the combination of innate ability, education, and experience that an individual possess at PhD completion. [↑](#footnote-ref-2)
3. Of course, Albert Einstein did not even have the support of a lower ranked university as he was only able to obtain a job at the Swiss Patent Office. [↑](#footnote-ref-3)
4. The finance field provides a fitting setting for the purpose of our study because it is sufficiently narrow to allow us to compare scholarly activity within the field. Comparing productivity across different areas is difficult as the standards across different disciplines vary. [↑](#footnote-ref-4)
5. The use of the initial five-year productivity as a proxy for talent is based on the premise that during the first five years, a researcher's productivity is driven mostly by talent, and the effect of the first affiliation on publication during this period (the nurturing of the new employer) is limited (i.e. would rather manifest itself a few years later). [↑](#footnote-ref-5)
6. For example, the NHL draft has been shown to have biases according to players’ birth date due to the timing of the draft (Deaner et al., 2013); individuals with noble-sounding surnames are found to work more often as managers than as employees (Silberzahn and Uhlmann, 2013); people with easy-to-pronounce names are judged more positively than those with difficult-to-pronounce names (Laham et al., 2012); and faculty members whose name appears earlier in the alphabet are significantly more likely to receive tenure at top departments (Einav and Yariv, 2006). [↑](#footnote-ref-6)
7. For example, outcomes that were considered in the past to be driven only by good nurturing, have be shown to be related to born qualities. Genes have been shown to be associated with educational attainment (Rietveld et al., 2013, Okbay et al., 2016), political attitudes (Fowler et al., 2008), gambling (Coming 1998), and economic behavior (e.g.; Dreber et al., 2009; Kuhnen and Chiao, 2009; Cesarini et al., 2009) among others. [↑](#footnote-ref-7)
8. University rank is based on its productivity level in terms of the number of top-tier publications affiliated with the university over our sample period. [↑](#footnote-ref-8)
9. Note that an author’s career is tracked from his/her first published article on the WOS. For convenience, we refer to this year as being tenure=0. [↑](#footnote-ref-9)
10. Changes to the exact definition of an A article matter little. We reran our analysis with a more restrictive definition of A articles – only the top 5 finance journals and the top 5 economics journals – and obtain very similar results to those presented in the paper. [↑](#footnote-ref-10)
11. An error in initial placement decisions may occur not only because of the inability to assess talent with precision, but also because of many other reasons. These include, for example, budget considerations of hiring institutions that do not correspond to the flow of talent of PhD graduates. [↑](#footnote-ref-11)
12. Note that the superior nurturing that may be expected in top-tier universities compared to second-tier universities during the first 5 years of employment, suggests that for a given level of productivity level (at year 5), the talent of individuals in second-tier universities may in fact be somewhat higher than that of top-tier individuals, which would bias against finding a nurturing effect on productivity. [↑](#footnote-ref-12)
13. The number of authors that have five or more A articles by year 5 in second-tier universities is too small (12 authors in total) to allow for any meaningful comparison. [↑](#footnote-ref-13)
14. For example, the question "would the researcher be granted tenure at your institution" that is often answered by external evaluators, does not allow for the consideration of the differences in nurturing that may exist between the institutions of the evaluated and the evaluator. [↑](#footnote-ref-14)