Research Value-Added in Elite Economics PhD Programs*

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Abstract

The 2025 One Big Beautiful Bill Act imposes endowment taxes on universities with large per-student assets, with the highest tax rates targeting five schools that train the most prolific economics researchers: Harvard, MIT, Princeton, Stanford, and Yale. Affected schools may respond by reducing graduate enrollment, potentially reducing research output. We use a novel sample of MIT Economics PhD program applicants to estimate the research value-added of eight elite schools. Our estimates mitigate selection bias by controlling for MIT admissions committee rankings—a remarkably strong predictor of long-run research success—and for applicant aspirations as revealed by their application portfolios. While rank controls substantially reduce estimated gaps between elite and non-elite graduates, large differences remain. Graduates of high-tax and other top-eight schools produce roughly 65% more impact-adjusted publications than do comparable students from non-top-eight US schools, with the elite advantage especially pronounced for top five journal publications. Within the elite tier, however, graduates of two untaxed schools perform comparably to those from highly-taxed schools on most measures, while research productivity within the high-tax group is (with one exception) remarkably similar. The out-performance of elite-school PhDs does not appear to be explained by editorial connections or peer effects in elite programs.

PRELIMINARY AND INCOMPLETE

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1 Introduction

The 2025 One Big Beautiful Bill Act (OBBA) imposes substantial taxes on private universities with large endowments. The top tax rate of 8% applies to schools with endowment assets exceeding $2 million per student. Five PhD-granting universities currently face this maximum rate: Harvard, MIT, Princeton, Stanford, and Yale. These institutions play an outsized role in training economics faculty. Graduates of economics PhD programs at high-tax schools account for over half of the faculty at highly-rated economics departments (Amir and Knauff, 2008).

In response to the endowment tax and other fiscal pressures, Harvard has considered plans to cut PhD admissions in many programs by half (Mao and Paulus, 2025). Other heavily-taxed schools may follow suit. Meanwhile, untaxed and lower-taxed schools with highly-rated doctoral programs in economics face their own challenges, including federal civil rights litigation and cuts to research funding. The combined effect may be a significant contraction in elite economics PhD training.

This paper uses novel data to gauge the extent to which admissions cuts by elite US PhD programs are likely to harm the economics research enterprise. Specifically, we ask whether doctoral programs at high-tax and other elite schools produce more prolific scholars as measured by publications in widely cited journals. As in the literature on K-12 school value-added (e.g., Angrist et al. (2024)), the parameters of interest are causal effects of attendance at one school or type of school versus another. In the spirit of the landmark Dale and Krueger (2002) study of undergraduate college value added, our identification strategy for causal value-added mitigates selection bias with controls for applicant quality and ambition. The MIT admissions committee's rank assigned to applicant finalists affords fine-grained control for the applicant preparation and aptitude for doctoral work.

The analysis reported here incorporates MIT admissions committee ratings assigned to the roughly 200 highest-ranked applicants to the MIT Economics PhD program in select application years from 1996-2020. MIT admissions' applicant ranking is a remarkably strong predictor of long-term research output (measured by an index heavily weighting top-journal publications). Admissions information, which also includes NSF awards and MIT admissions decisions, is matched to dissertation and research records drawn from the data analyzed in Angrist and Diederichs (2024). We also observe the set of doctoral programs to which applicants applied for a large subsample of applicants. As in Dale and Krueger (2002, 2014), Mountjoy and Hickman (2021), and Chetty, Deming and Friedman (2023), this offers a gauge of applicants' self-assessed commitment to and prospects for a research career.

The paper starts in Section 2 with a descriptive analysis of the matched applicant sample, focusing on graduates from programs at eight top schools: Berkeley, Chicago, Harvard, MIT, Northwestern, Princeton, Stanford, and Yale. This set includes the five schools most affected by the OBBA and three

others facing financial challenges, Berkeley, Chicago, and Northwestern.[1] Our elite eight is a subset of the Amir and Knauff (2008) list of top ten PhD programs measured by prestigious job market placement. Over three-quarters of the MIT applicants in our sample who earn PhDs get their degrees from one of these eight schools. Of these, around three-quarters earn degrees at a highly taxed school.

The analysis of school value-added detailed in Section 3 begins with uncontrolled comparisons by tax status. These comparisons show that high-tax schools graduate more prolific scholars. Inclusion of controls for applicant ability reduces this apparent advantage considerably, but still leaves substantial gaps. High-tax schools boost their graduates' top-journal publications by about 75% relative to non-elite schools. High-tax schools' advantage over foreign schools is even larger. Other elite-eight schools have similarly high value-added, on average. Roughly 40% of high-tax schools' value-added reflects increased numbers of publications, with the rest due to a shift towards publications in more widely-cited journals. Estimates of individual school value-added are more sensitive to admissions-rank controls than the estimates by tax group. In particular, gaps between Harvard and MIT (the two most selective schools) and other somewhat less-selective schools shrink considerably when estimated with controls.

Section **??** turns to possible explanations for differences in estimated value-added by tax group and school. This analysis begins with estimates that control for omitted variables bias due to unobserved applicant ambition and self-assessed prospects by controlling for the schools to which applicants have applied. Addition of application controls leaves the overall value-added picture unchanged. Section **??** also looks for outsized effects at home journals that may favor certain schools (the Quarterly Journal of Economics (QJE) for Harvard and MIT graduates, the Journal of Political Economy (JPE) for Chicago graduates, and the American Economic Association Papers and Proceedings (P&P), which has an editorial process that may broadly favor elites). This reveals some expected patterns. For instance, Harvard and MIT graduates indeed do especially well at the *QJE*. Publication outcomes omitting home journals nevertheless shows a strong elite-school advantage. At the same time, omission of home journals tends to flatten differences between schools within the elite group.

Finally, the paper assesses the importance of peer effects. The opportunity to study with talented classmates is often said to be a key feature of elite education at all levels (see, for instance, Abdulkadiroğlu, Angrist and Pathak (2014), Dobbie and Fryer (2014), and Ellison and Pathak (2025) for studies of peer effects at elite high schools). If the elite-school research advantage stems entirely from the assembly of talented cohorts, and if the best students migrate to untaxed schools following tax-induced enrollment cuts, aggregate research output may be unchanged by the endowment tax. Our

[1] The University of Chicago endowment is taxed at an intermediate 4% rate. Responding to a large deficit exacerbated by research cuts, Chicago has moved to trim some graduate programs (Glick and Eisenstadt, 2025). Northwestern and the University of California are on a list of schools targeted for civil rights litigation, announced in U.S. Department of Education (2025).

investigation of peer effects exploits idiosyncratic year-to-year within-school variation in peer composition. This analysis shows no relationship between peer quality (measured by the share of highly-ranked MIT applicants among an applicant's classmates) and research productivity. Value-added estimates are therefore unchanged when peer composition enters the value-added model.

Our analysis contributes to a literature examining the determinants of PhD student success in economics. This includes Laband (1985) and Conley and Önder (2014), both of which compare research success across PhDs from a wide range of schools. Athey et al. (2007) explores the predictive power of in-school performance measures for post-PhD outcomes. Angrist and Diederichs (2024) documents the fact that only 60% of recent graduates of elite PhD programs ever publish in a set of 137 core journals, and that graduates of the schools studied here are about equally likely to have at least one publication. Our results align with these studies in showing that research success has a large unpredictable component. We differ, however, in highlighting the average causal impact of elite school degree programs on a range of research outcomes, effects that remain large when value-added models are well-controlled.

This study also contributes to the literature on the economics of talent in a range of fields. This includes work examining early-life predictors of exceptional achievement, such as Lubinski and Benbow (2006), Agarwal and Gaule (2020), and Danieli et al. (2025). Our finding that the probability of research success is much larger for the very highest-ranked applicants has a similar flavor. Further afield, we contribute to a body of work studying scientific productivity. This includes studies of patenting and firm productivity such as Azoulay, Ding and Stuart (2007) and Baviskar et al. (2025).

Bell et al. (2019) highlights the problem of selection bias in research on patenting by showing that typically-unmeasured characteristics of inventors predict later-in-life patenting. A few studies tackle the problem of selection bias in productivity comparisons, as we try to do for research. These studies include Waldinger (2010) and Waldinger (2012), which use the Nazi-era expulsion of mathematicians and scientists from Nazi Germany to examine the effects of star researchers on PhD students and peer researchers. In the same spirit, Azoulay, Graff Zivin and Wang (2010) examines the productivity consequences of unexpected deaths of research collaborators. Other work along these lines includes the Borjas and Doran (2012) analysis of the post-1992 migration of Russian mathematicians to the US; the Chandra and Xu (2025) analysis of the research productivity of medical researchers who move their labs across institutions.

2 Data and Descriptive Statistics

2.1 Sample Construction

Our sample includes highly-ranked applicants in the 1996-1997, 2005-2010, and 2012-2024 MIT economics PhD application cohorts. All applicants were initially rated by one or two committee members, with high-ranking applicants rated by additional faculty readers. Data for most years include ratings for the 190-200 highest-ranked applicants, although finalist ratings for a few years are available for only 90-150 applicants. Finalists, many of whom have perfect GRE quantitative scores, are very strong prospects for graduate school. For purposes of statistical analysis, we average ratings across faculty readers, and convert this to within-cohort rank. Students with the same average rating are given the same rank.

Applicant rank reflects multiple independent evaluations made in an initial stage of MIT's rating process that ultimately whittles the list of finalists down much further. Ranks are not deterministically related to admission decisions, which are made through a process of committee discussion and review. Admissions committees aim to balance the class across fields of interest, among other considerations. In most years covered by our sample, admission decisions reflect candidate funding and department financial constraints. Prior to 2022, MIT depended on the National Science Foundation (NSF) and other outside funders to contribute financial aid for many admits. Our value-added models control for NSF awards and admission offers.

Applicants in the finalist sample are coded as having graduated from one of eight elite schools (five high-tax schools plus Berkeley, Chicago, and Northwestern), other US schools, or a foreign school. Our elite eight is a subset of the Amir and Knauff (2008) list of top ten PhD-producing schools in 2006 (a list that includes Oxford and the University of Minnesota). Some applicants fail to graduate. For those that do, applicant alma mater and graduation year come from EconLit dissertation records for American and Canadian PhDs, supplemented for elite eight graduates by the data set constructed for Angrist and Diederichs (2024), which augments EconLit with ProQuest and administrative records. For remaining applicants, school information comes from department websites and CVs. This information includes applicant gender. The applicant file is matched to EconLit using student names. The matched data set includes NSF fellowship status for most applicants. Further details regarding data processing, such as solutions for common or ambiguous names, appear in the Data Appendix.

Because economics journals vary widely in impact, an outcome of primary interest is a weighted publication count that applies citation-based influence weights to publication in 137 "deep impact" (DI) prominent journals, giving each author $1/n$ credit for an n-authored publication. Influence weights, which are similar to those used in Angrist et al. (2020), are proportional to the frequency with

which articles in each journal are cited by top five journals.[2] Journal influence weights are normalized so that the average article in a top five journal gets a weight of one. In practice, many citations in top five journals are to other top five outlets, so even prominent field and next-tier-general-interest journals get substantially lower weights. The five most highly weighted non-top five journals are *AEJ: Applied* (0.44), *Journal of Economic Perspectives* (0.30), *Journal of Economic Theory* (0.28), *RAND Journal of Economics* (0.28), and *AEJ: Policy* (0.24).[3] The influence weighting scheme generates our *weighted DI* measure of research success.

In addition to the weighted DI outcome variable, value-added is estimated for a range of raw publication counts. This includes counts of top five publications, unweighted DI publications, and all EconLit. Top five journals are the *American Economic Review (AER), Econometrica, Journal of Political Economy (JPE), Review of Economic Studies (RES)*, and the *Quarterly Journal of Economics (QJE)*. A few analyses omit two of the top five journals and articles in the *American Economic Association Papers and Proceedings*, publications in which do not get counted with the *American Economic Review* in either the Top Five or DI journal lists. These additional variables make no adjustment for joint authorship; all authors of a paper in, say, the *AER*, get credit for one top five publication.

2.2 The Graduates of Top Graduate Programs

The training of top economists has long been highly concentrated. Amir and Knauff (2008) reports that, in 2006, the majority of the tenure-track faculty in top ten US economics departments earned a PhD from one of the schools in our sample. An extended version of these statistics appears (with an alternate scaling) in the first column of Table 1. This column divides the Amir and Knauff (2008) number of top ten faculty who graduated from each of the elite eight by the number of top ten faculty who graduated from MIT, after adjusting for cohort size. Column 1 adds to this the share of top ten faculty trained at other US schools and at foreign schools (relative to the MIT share).[4]

Academic economics training remains concentrated. This can be seen in the second column of Table 1, which reports placement statistics for 1999–2018 graduates in our sample. Here, the top ten departments are US-only; this includes the elite eight plus the University of Pennsylvania and the University of Minnesota.[5] These numbers are scaled to give the share of graduates from each school

[2] More precisely, influence weights are a weighted average of the ratio of the fraction of each top five journal's recent citations that go to each journal, divided by the number of recent articles in the cited journal. Weights for each top five journal come from a page-rank style formula.

[3] A few new journals with short track records are assigned the average AEJ journal weight.

[4] As in Amir and Knauff (2008), these are weighted shares with weights proportional to the number of students in our dataset who attended each school. In addition to the elite eight, other leading US schools with the most top ten placements in our sample are Columbia (75), the University of Pennsylvania (63), NYU (61), and Michigan (36).

[5] Placement is inferred from institutional affiliations listed on publications in the six years after graduation. Graduates

employed at a top ten school relative to the share of MIT graduates. Although the ordering within this list changes from 2006, Harvard and MIT retain leading positions. The relative rate for the set of other elite averages 36% in our data and 38% in Amir and Knauff (2008).[6]

Consistent with the high rate of prestigious job placement, graduates of the elite eight have a strong research record. This can be seen in columns 3-6 of Table 1, the first of which records weighted DI publications by graduates from each school for the 1996-2019 application cohorts. These statistics are benchmarked by dividing by the publication rate of MIT PhDs. Columns 4-6 show comparable statistics for unweighted publication counts. Elite eight success by these measures is somewhat more concentrated than placement rates. It seems noteworthy that other US and foreign graduates do almost as well as the elite eight on the relatively unweighted DI and all Econlit measures.

The relative research success of elite-school PhDs reflects both extensive and intensive-margin differences. Figure 1 plots the distribution of weighted DI and top five publications for graduates of high-tax schools, other elite-eight schools, other US schools, foreign schools, and non-graduates. PhD graduates of high-tax schools are more prolific than graduates of other schools on both the intensive and extensive margins. A little under 80% publish at least 1 article in a deep impact journal or collective volume by the end of 2024, while other elite graduates have a similar hit rate. High-tax graduates are also more likely to notch more than one weighted DI publication, though again, other elite graduates are not far behind. Graduates of both elite groups are much more likely than other graduates to clear more than two weighted DI publications.

The relative performance of elite-eight graduates is even stronger when gauged by top five journal publications. The right panel of Figure 1 shows the distribution of top five articles for the same school groupings as the left. Fewer than half of high-tax graduates publish in the top five but roughly 30% publish two or more in these (in)famously selective outlets. Here, the gap between high-tax PhDs and other elite graduates is more pronounced. Graduates of both elite subsets, however, see top-five success markedly more often than do graduates of other sorts of schools.

2.3 Rankings and Outcomes

Research output is highly skewed, with top applicants publishing far more than the rest. This can be seen in the comparisons of mean and median DI and top five publication counts in Table 2. The last two columns of the table show that mean DI publications are triple the median (equal to one), while all EconLit publications average 4.5 times the median (also equal to one). This skewness is driven by the fact that highest-rank applicants are far more prolific than applicants ranked lower down. Measured

are automatically coded as placed at a top ten university if at least two publications report a top ten affiliation. Graduates with only one publication are classified manually.

[6] In absolute terms, top ten placement rates are 35% for MIT, 29% for Harvard, 14% for Princeton through Northwestern, and 5% for other US schools.

by weighted DI and top five output, students ranked 1–5 publish 3–4 times as much as those ranked 6 to 25. Multiples from the first to next group aren't quite as steep for the broader DI and all-Econlit measures, but remain substantial at a little over two.

The complementary cumulative distribution functions for weighted DI output plotted in Figure 2 suggest publication distributions conditional on rank satisfy stochastic dominance by rank. In other words, research output increases with rank at all points in the distribution of weighted DI publications. Consistent with Table 2, gaps in output at any level between ranks 1–5 and lower ranked applicants are largest. For instance the top-ranked group is roughly two-and-a-half times as likely to publish at least two papers as the next group. Distributions are nevertheless ordered, however, even in comparisons at lower ranks.

Half of the highest-rank applicants publishes two or more weighted DI papers, suggesting many in this group are headed for long research careers. The unweighted average DI count for ranks 1–5, shown in the third row of Table 2, is 9.3. On the other hand, many successful scholars were not ranked very highly when they applied to MIT. Roughly 10% of applicants ranked 51-200, few of whom were admitted to MIT, produce at least two weighted DI publications. It's noteworthy, however, that admissions rank predicts superstar research outcomes especially well. Over 30% of applicants ranked 1–5 publish at least six papers, a virtual zero-probability outcome for the rest. Consistent with this statistic, the probability an applicant lands in the top 10 in their cohort by weighted DI output hits 43%. This statistic, taken from the second row of Table 2, falls to 4% for applicants ranked below 50.

Our investigation of research productivity uses MIT admissions rank as a control for applicant ability and preparedness in cross-school comparisons. The type of school attended is indeed highly correlated with MIT admissions rank, though rank and school are far from deterministically linked. Figure 3, which presents the distribution of school attended by admissions rank (breaking out MIT), bears this out. Almost half of the highest-rank group studied at MIT, with most of the rest enrolling at another high-tax school. The share attending high-tax schools declines at lower ranks, but remains non-negligible even for applicants ranked below 150. The share graduating from other US and foreign programs and the share not graduating increase sharply as rank declines. Importantly for purposes of value-added estimation, Figure 3 shows substantial overlap in the distribution of schools conditional on rank.

3 Value-Added Models

Endowment taxes and growing financial pressure may lead affected schools to reduce PhD program enrollment. The research impact of such cutbacks depends in large part on whether high-tax and other elite schools have a causal effect on their PhD graduates' research success. Perhaps the relative

research success of elite graduates reflects graduate student selection and sorting, rather than value-added. If so, enrollment declines at the elites can be offset by funneling top students to unaffected programs. The University of Michigan economics department, for instance, would likely welcome the MIT entering class to Ann Arbor.

We cast causal effects in a Poisson value-added framework well-suited to count variables like publications, analogous to the linear models Angrist et al. (2017, 2024) and others use to assess the quality of K-12 schools. In our Poisson version, a constant-effects proportional model describes applicant i's potential outcome $k \in \{1, \ldots, K\}$ if he or she were to attend school $j \in \{1, \ldots, J\}$ as:

$$Y_{ij}^k = e^{\beta_j^k + \varepsilon_i^k}. \tag{1}$$

School j's value-added for research outcome k is defined as $e^{\beta_j^k} \equiv E[Y_{ij}^k]$. Error term ε_i^k captures non-school outcome-related factors such as aptitude, preparation, motivation, and ambition.

The observed outcome for student i is the potential outcome for i given the school i attends. Let D_{ij} denote an indicator equal to one if i enrolls at school j. Observed outcomes are then linked to potentials by:

$$Y_i^k = e^{\sum_j D_{ij} Y_{ij}^k} = \left[e^{\sum_j D_{ij}\beta_j^k}\right] \nu_i^k, \tag{2}$$

where $\nu_i^k \equiv e^{\varepsilon_i^k}$. Since graduate school enrollment is not randomly assigned, uncontrolled comparisons of mean outcomes across schools are likely to reflect selection bias. This is manifest as differences between $E[\nu_i^k | D_{ij} = 1]$ and $E[\nu_i^k | D_{ij'} = 1]$ for schools j and j'.

We mitigate selection bias by conditioning on a covariate vector, X_i, that includes measures of applicant aptitude, preparation, motivation, and ambition. These controls include the MIT admissions rating and admit status, NSF award status, and, in some cases, the set of schools to which MIT applicants applied. Given this information, the key conditional appendix assumption identifying causal value-added is:

$$E[\nu_i^k | X_i, D_i] = E[\nu_i^k | X_i] = e^{X_i'\gamma^k} \tag{3}$$

where γ^k is a vector of coefficients conformable with X_i and $D_i = (D_{i1}, ..., D_{iJ})'$ is the vector of school dummies for applicant i. We then have a causal conditional expectation function (CEF),

$$E[Y_i^k | X_i, D_i] = e^{\sum_j D_{ij}\beta_j^k + X_i'\gamma^k}, \tag{4}$$

in which proportional school value-added parameterized by the set of $\beta_j^k; j = 1, \ldots, J; k = 1, \ldots, K$.

Much of the analysis described below focuses on graduates from four groups of schools: high-tax, other elites, foreign, and other US. The parameters of interest here are coefficients on dummies indicating the set of schools in the first three groups, omitting other US category as a reference group.

The high-tax dummy, for instance, is the sum of dummies for MIT, Harvard, Stanford, Princeton, and Yale. High-tax value-added is the coefficient associated with this dummy.

3.1 High-Tax and Other Elite Eight Schools

Graduates of high-tax schools publish substantially more in higher-tier journals than do graduates of other groups of schools. The first column of Table 3 shows a precisely-estimated high-tax effect of 0.88 on weighted DI publications, implying a 141% publication gap relative to non-elite US schools.[7] This is estimated with covariates in the form of dummies indicating degree completion, US citizenship or permanent residence, gender and application year, omitting controls for aptitude and ambition (henceforth, an "uncontrolled" specification). The estimated uncontrolled gap in top five publications, shown in column 3, is even larger at 1.12. Graduates of other elite eight schools also produce more weighted DI and top five publications, with estimated Poisson coefficients of 0.49 and 0.62, respectively.

Inclusion of controls for linear, quadratic and reciprocal functions of rank, as well as NSF awards and MIT admission, knocks these effects down considerably. Although smaller when estimated with controls, value-added estimates for both sets of elite graduates remain substantial for both weighted DI and top five output. Estimates of elite value-added with unweighted DI, all EconLit, and any-publication outcomes, shown in columns 5-7 of the table, are markedly smaller than estimates for upper-tier measures. The relative success of elite PhD holders is manifest mainly in journal quality.

Differences within the elite group are compressed when estimated with rank and other key controls. Column 2, for instance, shows high-tax and other-elite effects on weighted DI publications of 0.56 and 0.47, respectively. The corresponding comparison for top five output, shown in column 4, is 0.72 and 0.59. With one exception, p-values testing the null hypothesis that high-tax and other-elite value added is the same, reported at the bottom of Table 3, are comfortably inframarginal when estimated with controls. The exception is for estimated impacts on a dummy indicating any publication, reported in column 7. By this measure, graduates of other elites beat graduates of high-tax schools, a marginally significant difference (the coefficient on other-elite value-added is the only significant effect on this extensive marginal outcome). The fact that tests of within-elite differences reject the null for models without controls suggests that the raw gap between graduates of high-tax and other elite schools is due mainly to selection rather than causal effects.

As can be seen in columns 2 and 4, reciprocal rank is clearly the most important mitigator of omitted variables bias (OVB) for estimates of high-tax value-added. Estimates of linear and quadratic coefficients in admissions rank, as well as coefficients on the MIT admit and NSF dummies, are small and insignificant in these and all other models. Surprisingly, estimated value-added for non-high-tax

[7] Poisson coefficient β_j^k implies a percentage increase in output equal to $e^{\beta_j^k} - 1$.

elites are much less sensitive to these controls than the estimated high-tax effect. This reflects the fact that students attending Berkeley, Chicago, and Northwestern were ranked similarly to many attending non-elite but well-regarded programs at schools like Columbia, Penn, NYU, and Michigan.

3.2 Estimates with Alternative Controls

On balance, well-controlled estimates for groups of schools suggest elite graduates produce more high-impact scholarship than graduates of other schools. At the same time, theses estimates suggest there is relatively little to choose between the elites. With controls for MIT admissions rank and other indicators of applicant aptitude, estimated value-added for high-tax and other elite schools is similar, with only one marginally significant difference between them.

Estimates of high-tax value-added that control for a measure of applicants' self-assessed prospects and ambition provide a partial check on a causal interpretation of these findings. In the spirit of Dale and Krueger (2002), which controls for undergraduate application targets in estimates of college quality, we estimate high-tax and other-elite value-added in models that control for the list of schools to which MIT applicants applied. The 85% of MIT applicants may be particularly ambitious or confident, while the 35% who did not apply to Berkeley may be less committed to an economics PhD, come what may. Data on target schools is available for most applicants in the 2013-2019 application cohorts. Applicants for whom target-school information is available applied to 69 schools besides MIT.

Estimates with application targets, reported in Table 4, are similar to estimates on the same sample that omit these controls. As in Dale and Krueger (2002), Table 4 labels these "self-revelation controls." All estimates in this table are from models that include functions of rank and other controls for applicant potential included in the models generating Table 3. As can seen in column 2 of the table, elite value-added for weighted DI output with self-revelation controls is estimated to be 0.68 for high-tax schools and 0.54 for other elites. These can be compared with corresponding estimates of 0.61 and 0.44 in models that omit these controls. Estimates of value-added for other outcomes are even less sensitive to inclusion of self-revelation controls.

Reciprocal rank appears to be be the linchpin of the conditional independence assumption that supports a causal interpretation of the estimates in Tables 3 and 4. In support of this claim, Appendix Table A1 reports estimates of elite value-added from models with and without NSF and MIT admission dummies. These have little explanatory power; the coefficient estimates associated with these variables are small and not significantly different from zero, while estimated value-added is insensitive to their inclusion. These findings suggest that MIT admissions rank captures applicant most if not all applicant characteristics related to research success.

4 Explaining School Quality

Why do graduates of some PhD programs outperform graduates from others?

4.1 Probing Possible Peer Effects

peer effects in grouped models–T5

Idiosyncratic variation in where highly ranked students choose to go in each year identifies the importance of peer composition for research success. For example, in 2010 MIT attracted only two rank 1-10 students, whereas in 2016 MIT attracted all ten.[8] Harvard jumped from just four rank 1-25 students in 1996 to ten in 1997. And Yale jumped from just three rank 1-150 students in 2016 to sixteen in 2017. To look for potential peer effects we construct three measures of the strength of the peers in each student's cohort: the fraction of the rank 1-10 students in the cohort who attended the student's school; the fraction of the rank 1-25 students in the cohort at the school; and a weighted fraction of the top 200 students in the cohort at the school, using inverse ranks as the weights. The motivation for the latter is that it is similar to using predicted peer publications (as predicted given ranks but not school attended) as the strength-of-peers variable.

We find little evidence for peer effects in our data and they do not appear to be driving our estimates, but we also cannot rule out that they are present. A naive estimation of peer effects, not allowing for the possibility of school effects, would conclude that substantial peer effects are present. Column (1) of Table 5 shows estimated coefficients on the three peer effects measures in three separate Poisson regressions that do not allow for school effects: one using each peer-effects variable on the RHS. All use our standard weighted publication measure as the dependent variable and include our standard set of controls including application rank controls. In these regressions the peer effects appear large and significant, reflecting that the students at the programs that attract most top students publish more in top journals. For example the 0.6 point estimate in the regression using Top 25 Peers would suggest that students at a school that attracted half of the top 25 students in a cohort would have publications that were more than 30% higher. But when we add school dummies in column (3) so the identification is coming only from the year-to-year variation in the strength of the students a school attracts, the estimated coefficients are much smaller and become insignificant. Meanwhile, the estimated effects of high-tax and other elite eight schools remain almost identical to what they were in Table 3 (and reproduced here in column (2)). Hence, the regressions provide no indication that peer effects are driving our main value-added estimates. The standard errors on the peer effect coefficients are fairly large, however, so we cannot say that peer effects do not also matter to graduate students.

Remaining columns of Table 5 oiffer no evidence of peer effects in borader journal outcomes.

[8] Due to ties, our measure assigns 11 students to ranks 1-10 in 2016.

individual school effects–T6

School-level value-added estimates for weighted DI and other outcomes in Table 6 shed some light on this. These estimates are from specifications paralleling those used to construct Table 3.

Many of the traditional elite eight schools have large and significant value-added. Column (2) of Table 6 shows the estimates of weighted publication value-added.[9] Students who attend Harvard, MIT, and Princeton are estimated to produce about twice as many weighted publications ($e^{0.69} \approx 2$) on average as similarly ranked students who attend a non-elite eight US school. The value-added estimates for Berkeley, Stanford, and Northwestern are also significant at levels ranging from 1% to 10%.

Most of the publication advantage of MIT and Harvard relative to the next highest schools is attributable to student selection. The MIT value added estimate is almost 40% smaller than the raw publication advantage not controlling for rank shown in column (1). The coefficients for schools other than MIT, Harvard, and Stanford are less affected by the rank controls.

The school level value added estimates are somewhat but not highly aligned with endowment tax exposure. Non-aligned estimates include Yale, which is in the highest tax bracket but has the smallest point estimate for value added, and Berkeley and Northwestern, which are not and have point estimates higher than Stanford's. This might be taken to suggest that a large per-student endowment is only part of what helps schools develop high value-added PhD programs. Standard errors on the individual school estimates are sufficiently large so that few of the pairwise comparisons are statistically significant.

The school-level value-added rankings look somewhat different if we look for effects on all Econlit publications instead of publications in highly-cited journals. In column (3), Berkeley appears to have the largest value added in the dimension of increasing the probability that students will publish something. In the regression examining all-Econlit publication counts (column (4)), the largest two estimated effects are those for Princeton and Berkeley, and it is only these estimates that are significant at the 5% level. Focusing narrowly on publications in top five journals makes the estimates for Harvard and MIT the largest. Again, these observations should be treated cautiously given that the standard errors are sufficiently large so that most pairwise difference comparisons of elite eight schools are not statistically significant at the 5% level.

school effects vs selectivity–Figure 4

Within the elites, the relationship between program selectivity and weighted DI value-added is remarkably flat. Figure 4 plots school-level value-added estimates, computed with and without controls against with the selectivity of PhD programs as measured by the average MIT admissions rank assigned

[9] The school value-added regressions use the same five controls for student quality as the group value-added regressions in Table 3.

to each school's graduates. Without controls, estimated value-added increases steeply with selectivity, peaking with the estimate for MIT.

4.2 Journal Home Teams

Table 7

Journals associated with elite economics departments may afford a home team advantage to PhDs from these programs. Perhaps graduates of elite schools are publishing more in widely-cited journals not because the research they are producing is more important or of better quality, but because they are more closely connected to journal editors who exhibit favoritism in choosing which papers to publish.[10] If weighted publication differences are entirely due to favoritism there would again be no loss from restricting admissions at high-tax schools. Three complaints sometimes alleged are the *Quarterly Journal of Economics* (*QJE*) favoring people with Harvard (and MIT?) connections, the *Journal of Political Economy* (*JPE*) favoring people with Chicago connections, and the *AEA Papers and Proceedings* (*P&P*) favoring people at elite schools whose faculty often serve as AEA officers.

There are clear patterns in where students from top schools are publishing that are aligned with the favoritism world view. Column (1) of Table 7 examines value-added in the dimension of boosting students' publications in the *QJE*. It indeed shows that attending Harvard has an extremely large effect on *QJE* publications, and also reveals an effect of attending MIT with a slightly larger point estimate and large effects of attending Princeton, Berkeley, and Chicago. Column (2) examines value-added in boosting *JPE* publications. Here, we find a large effect of attending Chicago, but again the point estimate for Chicago is not the largest and three other schools have estimates significant at the 5% level. Column (3) shows effects on *P&P* publications. Here, the effects for MIT, Harvard, Berkeley, and Stanford are all highly significant with point estimates larger than those schools' effects on weighted publications.

If the effects identified above are entirely due to favoritism, then our overall estimate of the value-added of elite eight programs would be somewhat smaller, but the main conclusion that elite eight PhD programs have substantial value added would remain. Column (5) reruns our school-level value added regression with a modified dependent variable that places zero weight on publications in the *QJE*, *JPE*, and *P&P*. The value-added estimates are about 20% smaller on average than the estimates from Table 6 (reproduced on column (4)) but they are still substantial and most remain significant at the same level. Relative rankings are somewhat different in columns (4) and (5), with Princeton having the largest estimated value added when one drops the *QJE*, *JPE*, and *P&P*. Keep in mind, however, that most pairwise differences are not significant. Columns (6) and (7) present an alternate no-home-

[10] See Colussi (2018) on ties between journal authors and editors.

journals comparison, this time comparing the value-added one gets when counting only publications in *American Economic Review*, *Econometrica*, and *Review of Economic Studies* to what we got when considering all top five publications. The most striking finding here is that several of the schools have a quite large value added in training students to publish in the *AER*, *Econometrica*, and *Review of Economic Studies*.

5 Summary and Conclusions

A handful of PhD programs play a dominant role in economics graduate training. It has long been known that their graduates hold many of the faculty positions at top schools. Universities that have traditionally educated the majority of top-department faculty are among the five most targeted by the recently adopted university endowment taxes. Harvard's announced cutback in their class size naturally raises the question of whether there will be a substantial long-run impact on economics research if they and other traditional elite schools are forced to scale back their PhD programs.

In this paper we noted a number of updated and new facts about the productivity of graduates of various programs. Updating Amir and Knauff (2008) we find that graduates of the traditional elite continue to be much more likely to obtain top 10 jobs. And in something of a contrast to Conley and Önder (2014), our updated look at publications indicates that graduates of the traditional elite publish many more papers in high-impact journals than do graduates of other US and foreign universities.[11] New facts on average publications include that the publication gap between graduates of elite eight US and foreign universities is even larger, and that the publication advantage of top-school graduates includes both a moderate advantage in the number of papers published and a larger advantage in the average impact of the journals in which graduates publish.

Studies including Athey et al. (2007), Conley and Önder (2014), and Angrist and Diederichs (2024) argue that an economics PhD applicant's research success is hard to predict. If this were true in the extreme and success in graduate school was completely unpredictable, the differences in average publications we find would imply very large differences in value-added. We also, however, make a number of new observations about the predictability of graduate student success that are somewhat at odds with the impression many seem to have formed from the previous literature. We note that publications in top journals are, in fact, quite predictable – ratings given by MIT evaluators at the time when students applied to graduate school have strong predictive power even within the uniformly strong set of students in our dataset. This predictability comes both from changes in the extensive margin – will students ever publish a paper – and changes in the intensive margin. One striking

[11] Note that this latter finding is despite our only considering highly-ranked PhD applicants, whereas Conley and Önder (2014) consider all 1984-2000 graduates of the elite and non-elite schools.

pattern in the extensive margin is that students at the very, very top, e.g. students ranked among the top-5 in their entering cohort, are much more likely to be extremely successful. Another noteworthy finding is that we do see some students at all ranks in our data going on to have very successful careers. We also note that highly ranked applicants are quite concentrated in highly-ranked PhD programs.

The facts that success is predictable and the highest-ranked students disproportionately attend elite eight schools makes it plausible that the output gap between graduates of elite eight and other schools is due to elite illusion, rather than to true differences in value added. We find that gaps in student quality do explain a substantial portion of the achievement gap, particularly the gap between MIT/Harvard and other elite eight schools. But they only account for a part of the gap between the publications of highly-ranked applicants who attend elite eight vs. other US schools and the residual gaps in what we refer to as value added are very large. Students who attend high-tax and other elite eight schools eventually produce 60-75% more journal-impact-adjusted papers than seemingly similar students who attended non-elite eight programs. About two-thirds of the value-added of elite eight schools seems to derive from helping students to publish in higher-impact journals. But there are also measurable effects on increasing students' total publications. Losses from a reduction in the number of students who are trained at high-tax schools would be particularly large if the displaced students are no longer able to study in the US.

The impact of PhD program cutbacks depends on the mechanisms that underlie the current differences in value added. Impacts might be less than our regressions predict if the current value added is mostly due to peer effects, but our analysis of peer effects does not suggest that peer effects are very important. We would also not worry about losses if the value added we have measured was attributable to unobserved differences in student quality and/or to elite schools giving students a leg up in a biased publication process. We found little evidence that either is driving results. The impact of the endowment tax could also plausibly be larger than one would forecast using our regressions as estimates of lost value added. One source of the value added we have identified may be benefits that large per-student-endowments provide: funding graduate student data acquisition, providing fellowships that give students more time to focus on research, etc. Endowment taxes could harm graduate training via such a channel even if the most affected schools do not reduce their class sizes.

We see no reason to think that the economics profession is unique. The schools targeted by the endowment tax also have many elite science and engineering programs. If elite PhD programs in other disciplines also have substantial value-added, then the endowment tax (and cutbacks in NSF and NIH funding) could have a substantial impact on the next generation of US science and engineering researchers. Had we been trying to publish this paper in the *QJE*, we could have titled it "Will The University Endowment Tax Slow Scientific Progress? Evidence from Economics." We didn't because it would be heroic to suggest that value-added patterns for science and engineering programs

are likely to be similar to those in economics. It could be that success in many other disciplines is similarly predictable from information available at the time of graduate school application. It could be that value-added differences are similarly smaller than one would naively infer from differences in the average productivity of graduates, but still substantial. We think these are very important questions to explore and hope that others will take them up.

References

Abdulkadiroğlu A, Angrist J, Pathak P. 2014. "The Elite Illusion: Achievement Effects at Boston and New York Exam Schools." *Econometrica*, 82(1): 137–196.

Agarwal R, Gaule P. 2020. "Invisible Geniuses: Could the Knowledge Frontier Advance Faster?" *American Economic Review: Insights*, 2(4): 409–424.

Amir R, Knauff M. 2008. "Ranking economics departments worldwide on the basis of PhD placement." *The Review of Economics and Statistics*, 90(1): 185–190.

Angrist J, Azoulay P, Ellison G, Hill R, Lu SF. 2020. "Inside Job or Deep Impact? Extramural Citations and the Influence of Economic Scholarship." *Journal of Economic Literature*, 58(1): 3–52.

Angrist JD, Hull PD, Pathak PA, Walters CR. 2017. "Leveraging Lotteries for School Value-Added: Testing and Estimation." *The Quarterly Journal of Economics*, 132(2): 871–919.

Angrist J, Diederichs M. 2024. "Dissertation Paths: Advisors and Students in the Economics Research Production Function." National Bureau of Economic Research.

Angrist J, Hull P, Pathak PA, Walters C. 2024. "Credible School Value-Added with Undersubscribed School Lotteries." *The Review of Economics and Statistics*, 106(1): 1–19.

Athey S, Katz LF, Krueger AB, Levitt S, Poterba J. 2007. "What does performance in graduate school predict? Graduate economics education and student outcomes." *American Economic Review*, 97(2): 512–518.

Azoulay P, Ding W, Stuart T. 2007. "The Determinants of Faculty Patenting Behavior: Demographics or Opportunities?" *Journal of Economic Behavior & Organization*, 63(4): 599–623. NBER Working Paper No. 11348 (2005).

Azoulay P, Graff Zivin JS, Wang J. 2010. "Superstar Extinction." *Quarterly Journal of Economics*, 125(2): 549–589.

Baviskar S, et al. 2025. "Elite Talent and Firm Productivity in the Age of AI." Working Paper.

Bell AM, Chetty R, Jaravel X, Petkova N, Van Reenen J. 2019. "Who Becomes an Inventor in America? The Importance of Exposure to Innovation." *Quarterly Journal of Economics*, 134(2): 647–713.

Borjas GJ, Doran KB. 2012. "The Collapse of the Soviet Union and the Productivity of American Mathematicians." *Quarterly Journal of Economics*, 127(3): 1143–1203.

Chandra A, Xu C. 2025. "Where Discovery Happens: Research Institutions and Fundamental Knowledge in the Life-Sciences." National Bureau of Economic Research Working Paper 33996, July.

Chetty R, Deming DJ, Friedman JN. 2023. "Diversifying Society's Leaders? The Determinants and Causal Effects of Admission to Highly Selective Private Colleges." National Bureau of Economic Research Working Paper 31492, July.

Colussi T. 2018. "Social Ties in Academia: A Friend is a Treasure." *Review of Economics and Statistics*, 100(1): 45–60.

Conley JP, Önder AS. 2014. "The Research Productivity of New PhDs in Economics: The Surprisingly High Non-Success of the Successful." *Journal of Economic Perspectives*, 28(3): 205–16.

Dale SB, Krueger AB. 2002. "Estimating the Payoff to Attending a More Selective College: An Application of Selection on Observables and Unobservables." *The Quarterly Journal of Economics*, 117(4): 1491–1527.

Dale SB, Krueger AB. 2014. "Estimating the Effects of College Characteristics Over the Career Using Administrative Earnings Data." *Journal of Human Resources*, 49(2): 323–358.

Danieli O, Brosh N, Maagan D, Shorrer R, Zussman N. 2025. "The Long-Term Effecs of Gifted Students Programs." Tel Aviv University.

Dobbie W, Fryer RG. 2014. "Exam High Schools and Academic Achievement: Evidence from New York City." *American Economic Journal: Applied Economics*, 6(3): 58–75.

Ellison G, Pathak PA. 2025. "Optimal School System and Curriculum Design: Theory and Evidence." National Bureau of Economic Research Working Paper 34091, August.

Glick I, Eisenstadt E. 2025. "UChicago to Cut Some Ph.D., Master's Admissions for 2026–27." *Chicago Maroon*, https://chicagomaroon.com/48307/news/uchicago-to-cut-some-ph-d-masters-admissions-for-2026-27/.

Laband DN. 1985. "An Evaluation of 50 "Ranked" Economics Departments: By Quantity and Quality of Faculty Publications and Graduate Student Placement and Research Success'." *Southern Economic Journal*, 52(1): 216–240.

Lubinski D, Benbow CP. 2006. "Study of Mathematically Precocious Youth after 35 Years: Uncovering Antecedents for the Development of Math-Science Expertise." *Perspectives on Psychological Science*, 1(4): 316–345.

Mao WC, Paulus VH. 2025. "Harvard To Admit 50% Fewer Ph.D. Students in Science, Walking Back Deeper Cuts." *The Harvard Crimson*, https://www.thecrimson.com/article/2025/11/19/fas-science-phds/.

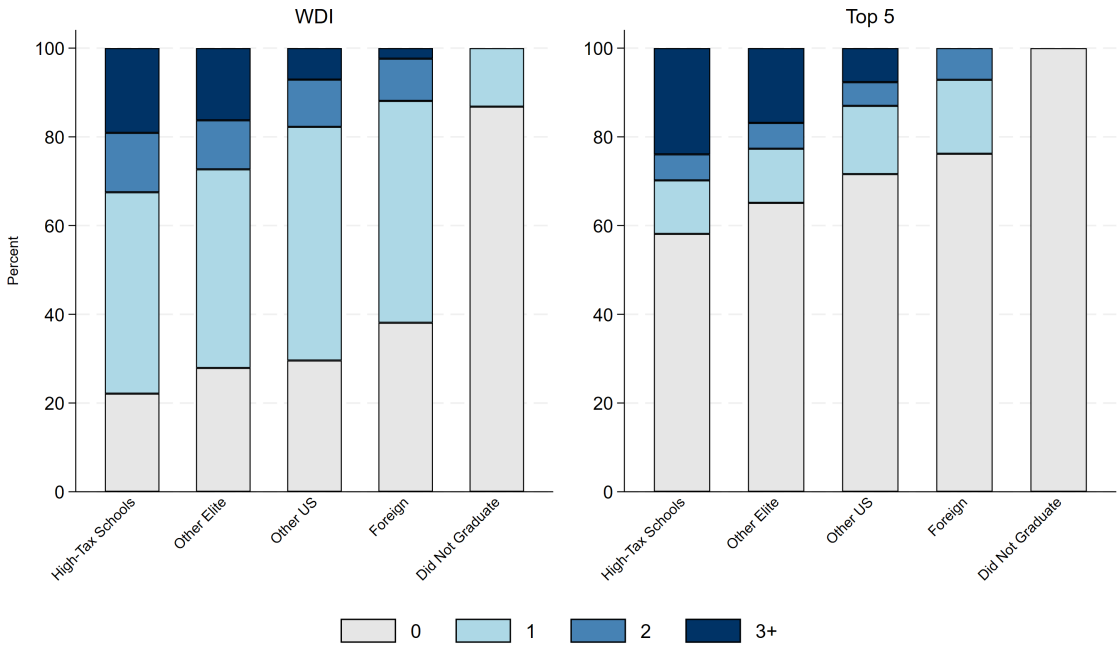
Mountjoy J, Hickman BR. 2021. "The Returns to College(s): Relative Value-Added and Match Effects in Higher Education." National Bureau of Economic Research Working Paper 29276.

U.S. Department of Education. 2025. "U.S. Department of Education's Office for Civil Rights Sends Letters to 60 Universities Under Investigation for Antisemitic Discrimination and Harassment."

Waldinger F. 2010. "Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany." *Journal of Political Economy*, 118(4): 787–832.

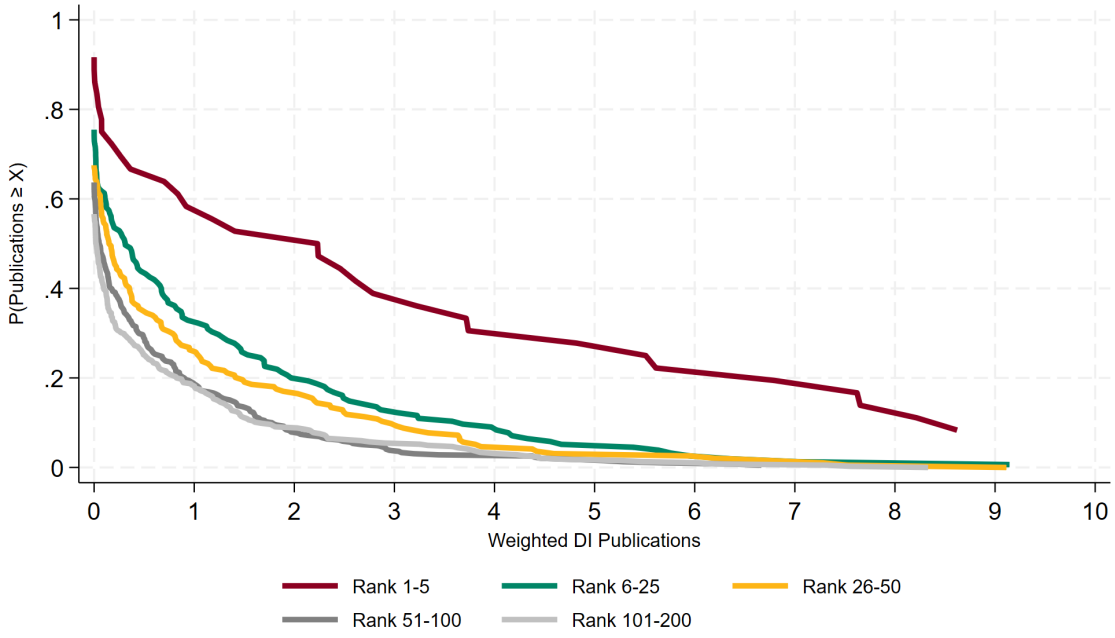
Waldinger F. 2012. "Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany." *Review of Economic Studies*, 79(2): 838–861.

Figure 1: Distribution of Publications by School Type: WDI and Top 5



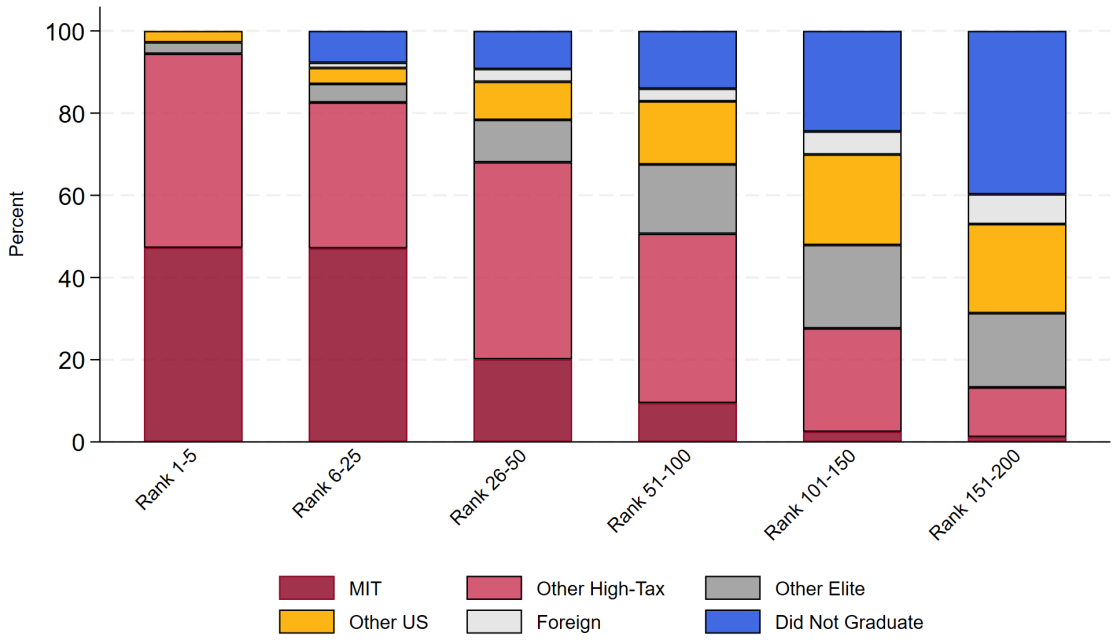
Notes: This figure shows stacked bar charts of the distribution of publications across five school type categories: High-Tax Schools (MIT, Harvard, Stanford, Princeton, and Yale), Other Elite (Chicago, Northwestern, and Berkeley), Other US, Foreign, and Did Not Graduate. The left panel displays coauthorship- and journal-influence-adjusted publications (WDI) and the right panel displays top five journal publications. Both panels show the share of applicants in each publication bin: 0, 1, 2, and 3+. WDI statistics are continuous and fall into intervals, e.g. $(1, 2]$. Application cohorts up to 2010.

Figure 2: Complementary Cumulative Distribution of Publications by Admissions Rank



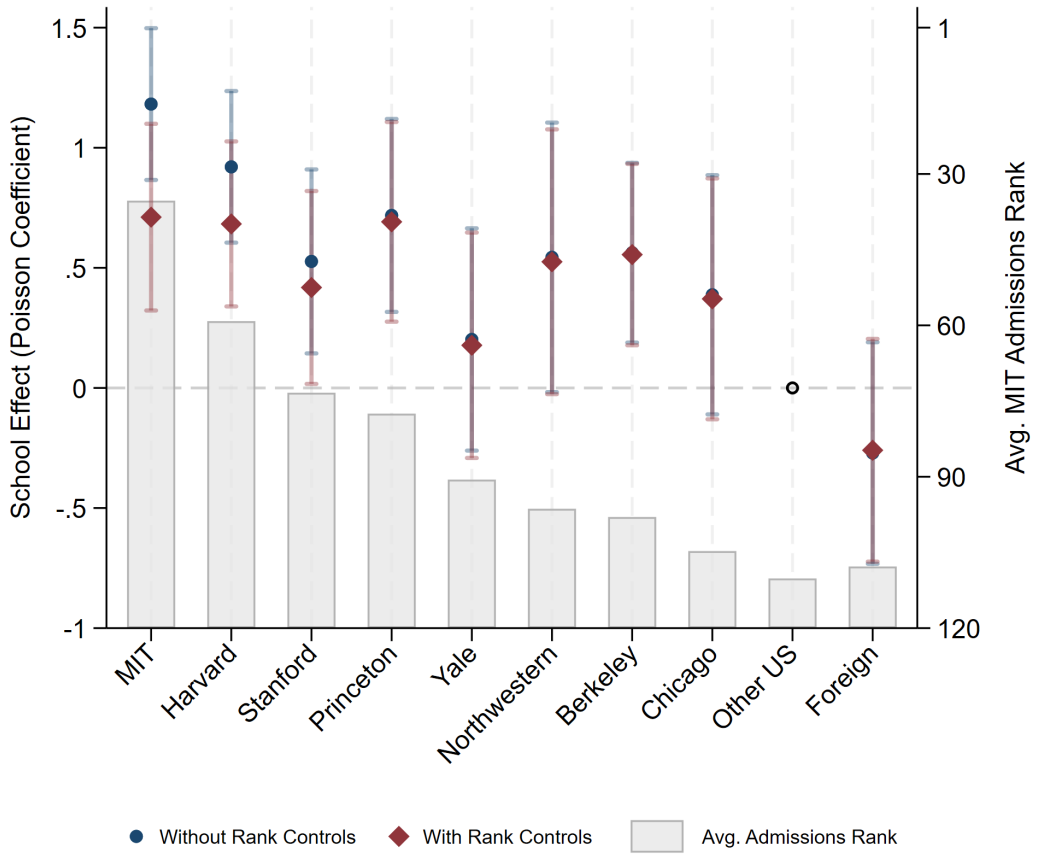
Notes: This figure shows the complementary cumulative distribution function (1-CDF) of WDI publications for five admissions rank groups (1–5, 6–25, 26–50, 51–100, 101–200). The y-axis represents the probability of having at least X WDI publications. The x-axis is truncated at 10. Application cohorts up to and including 2010.

Figure 3: Graduate School Attended by Admissions Rank



Notes: This figure presents stacked bar charts of the distribution of graduate school attendance across six admissions rank groups (1–5, 6–25, 26–50, 51–100, 101–150, 151–200). MIT is separated from other high-tax schools (Harvard, Stanford, Princeton, and Yale). Other elite eight schools are Chicago, Northwestern, and Berkeley. The remaining school groups are other US, foreign, and did not graduate. Data are for application cohorts up to 2010.

Figure 4: School Effects by School Selectivity



Notes: This figure plots Poisson regression coefficients for each of the elite eight schools and foreign schools taken from Table 6 for WDI value-added. The reference category is other US. Schools are ordered left to right by average MIT admissions rank of their graduates (most selective first); gray bars mark average rank (on the right axis, reversed so that lower ranks appear as taller bars). Vertical lines show 95% confidence intervals based on robust standard errors. The sample includes application cohorts before 2020. $N = 2{,}582$.

Table 1: Relative Success of Elite Economics PhDs

	Top 10 Placement					
	Amir-Knauff All 2006 Faculty	Our Data 1999-2018 Graduates	Publications Relative to MIT			
			WDI	T5	DI	All EconLit
School	(1)	(2)	(3)	(4)	(5)	(6)
MIT	100	100	100	100	100	100
Harvard	78	82	72	76	82	84
Princeton	51	26	60	52	85	92
Stanford	47	56	40	39	59	64
Chicago	41	33	43	45	62	77
Yale	39	29	30	22	53	66
Berkeley	20	58	47	41	68	84
Northwestern	18	28	56	39	72	77
Other US	7	15	28	22	49	63
Foreign	5	6	19	13	49	79

Notes: Each row expresses a school group's mean outcome as a percentage of the MIT mean. Column (1) reports shares from Amir and Knauff (2008). Column (2) measures top-10 placement in our sample: we classify a graduate as placed at a top-10 department if they have at least two publications affiliated with the same top-10 school within six years of graduation, or one such publication confirmed by manual verification. Top ten departments are defined as the elite eight plus the University of Pennsylvania and the University of Minnesota. Column (2) restricts the sample to graduates with degree year < 2019. Column (3) reports relative average weighted DI publications. Columns (4)–(6) report relative counts of publications in top five journals, 137 DI journals, and all EconLit journals, respectively. Columns (3)–(6) restrict the sample to application cohorts before 2020. $N = 2{,}582$.

Table 2: Publications by MIT Admissions Rank

	Mean Publications by Rank							
	1-5	6-25	26-50	51-100	101-150	151-200	Mean	Median
Coauthorship- and impact-adjusted pubs (WDI)	2.03	0.72	0.54	0.36	0.28	0.22	0.45	0.01
Fraction in top 10 of cohort (ranked by WDI)	0.43	0.11	0.08	0.04	0.04	0.02	0.06	0.00
Top 5 Count	3.44	1.10	0.82	0.53	0.38	0.22	0.66	0.00
DI Count	9.31	3.95	3.47	2.56	2.25	2.34	2.99	1.00
All Econlit	11.87	5.08	4.84	3.89	3.59	4.43	4.43	1.00

Notes: This table shows publication statistics by MIT admissions rank and overall for application cohorts through 2019 and publications through 2024. The first six columns report means by rank bin; the last two columns report overall sample means and medians. The first row reports coauthorship- and journal-influence-adjusted publications (WDI). The second row shows the fraction of students in each bin who rank in the top 10 of their application-year cohort when ranked by WDI. Remaining rows report publication counts in Top 5 journals, DI journals, and all EconLit. $N = 2{,}582$.

Table 3: High-Tax Value-Added

	WDI		Top 5		DI	All Econlit	Any Pub
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Tax School	0.88***	0.56***	1.12***	0.72***	0.34***	0.22**	0.04
	(0.14)	(0.15)	(0.18)	(0.20)	(0.11)	(0.10)	(0.04)
Other Elite	0.49***	0.47***	0.62***	0.59***	0.26**	0.20*	0.12**
	(0.17)	(0.17)	(0.23)	(0.23)	(0.12)	(0.11)	(0.05)
Foreign School	-0.27	-0.26	-0.36	-0.35	0.08	0.31	-0.02
	(0.24)	(0.24)	(0.33)	(0.33)	(0.23)	(0.29)	(0.09)
Admitted to MIT		0.16		0.22	0.08	0.04	0.05
		(0.12)		(0.14)	(0.10)	(0.09)	(0.04)
NSF Winner		0.13		0.10	0.10	0.07	0.05
		(0.12)		(0.14)	(0.10)	(0.09)	(0.04)
1/Rank		1.70***		1.78***	1.23***	1.23***	0.25***
		(0.24)		(0.26)	(0.24)	(0.23)	(0.09)
Rank/100		-0.53		-0.39	-0.43	-0.33	-0.10
		(0.35)		(0.43)	(0.29)	(0.28)	(0.13)
$(\text{Rank}/100)^2$		0.19		0.06	0.24	0.23	0.06
		(0.18)		(0.23)	(0.15)	(0.15)	(0.07)
Dep. var. mean	0.45	0.45	0.66	0.66	2.99	4.43	0.63
p-value High Tax = Other Elite	0.003	0.528	0.002	0.434	0.372	0.799	0.060

Notes: Each column reports Poisson regression results for regressions of publication outcomes on indicators for high-tax, other elite eight, and foreign school groups, with other US schools as the omitted category. All specifications control for graduation status, US citizenship or permanent residence, gender, and application-year fixed effects. Columns (1)–(2) use coauthorship- and journal-influence-adjusted publications (WDI) as the dependent variable; columns (3)–(4) use the Top 5 count. In each pair, the odd column excludes rank and admission controls, while the even column adds rank controls, MIT admission status, and NSF fellowship receipt. Columns (5)–(7) include rank and admission controls and use as dependent variables: DI journal count, all EconLit count, and any publication, respectively. The sample includes application cohorts before 2020. The Wald χ^2 statistic tests the null that the high-tax and other-elite-eight coefficients are equal. Standard errors are robust to heteroskedasticity. $N = 2{,}582$.

Table 4: High-Tax Value-Added with Self-Revelation Controls (2013-2019 applicants)

	WDI		Top 5		DI		All Econlit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Tax School	0.61***	0.68***	0.92***	0.99***	0.26*	0.29*	0.13	0.12
	(0.23)	(0.22)	(0.33)	(0.35)	(0.16)	(0.16)	(0.14)	(0.14)
Other Elite	0.44	0.54**	0.81**	0.82**	0.14	0.16	-0.01	-0.04
	(0.27)	(0.26)	(0.37)	(0.37)	(0.16)	(0.16)	(0.14)	(0.15)
Foreign School	0.31	0.43	0.81	0.93	0.82*	0.85*	1.04*	0.99**
	(0.37)	(0.35)	(0.61)	(0.62)	(0.50)	(0.46)	(0.62)	(0.46)
Self-Revelation Controls		✓		✓		✓		✓
Dep. var. mean	0.12	0.12	0.18	0.18	0.95	0.95	1.49	1.49
p-value High Tax = Other Elite	0.491	0.583	0.681	0.533	0.356	0.339	0.320	0.277

Notes: This table examines the sensitivity of value-added estimates to inclusion of self-revelation controls. The sample is limited to 2013–2019 application cohorts. All models include the admissions rank and related control variables used for Table 3. Odd-numbered columns omit self-revelation controls; even-numbered columns add indicator variables for each program to which the student reported applying, along with an indicator for students who did not report other program applications. The dependent variables are, in column pairs: WDI (1–2), Top 5 (3–4), DI (5–6), and All EconLit (7–8). Standard errors are robust to heteroskedasticity. $N = 1{,}262$.

Table 5: Peers or Schools?

	WDI		Top 5		All EconLit	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Top 10 Peers						
Share Top 10 peers	0.52**	0.09	0.65**	0.07	-0.12	-0.28
	(0.25)	(0.40)	(0.28)	(0.44)	(0.18)	(0.28)
High Tax School		0.56***		0.73***		0.26**
		(0.18)		(0.23)		(0.13)
Other Elite		0.48***		0.61***		0.20*
		(0.17)		(0.23)		(0.11)
p-value High Tax = Other Elite	.	0.627	.	0.542	.	0.563
Panel B: Top 25 Peers						
Share Top 25 peers	0.60*	0.00	0.67*	-0.26	-0.17	-0.70
	(0.31)	(0.63)	(0.36)	(0.72)	(0.22)	(0.46)
High Tax School		0.59***		0.81***		0.35**
		(0.20)		(0.25)		(0.15)
Other Elite		0.48***		0.61***		0.20*
		(0.17)		(0.23)		(0.11)
p-value High Tax = Other Elite	.	0.578	.	0.362	.	0.272
Panel C: Top 200 Peers (Reciprocal Weighted)						
Share Wgt. Top 200 peers	0.95**	0.42	1.12**	0.22	-0.10	-0.38
	(0.40)	(0.71)	(0.47)	(0.80)	(0.29)	(0.53)
High Tax School		0.51**		0.71***		0.26*
		(0.20)		(0.25)		(0.15)
Other Elite		0.48***		0.60***		0.20*
		(0.17)		(0.23)		(0.11)
p-value High Tax = Other Elite	.	0.865	.	0.625	.	0.636
Dep. var. mean	0.45	0.45	0.66	0.66	4.43	4.43

Notes: This table reports Poisson estimates of peer effects on Ph.D. graduates' research productivity, estimated with and without school-group indicators. The peer-share for student i equals the number of top-X MIT applicants at the same school and cohort (excluding i), divided by X if i is outside the top X or by $X-1$ if i is inside. Estimates in Panels A and B use top-10 and top-25 peers, respectively. Estimates in Panel C top-200 peers, weighted by 1/rank, divided by the maximum possible weight ($\sum_{j=1}^{200} 1/j$, minus the weight for applicant i). Higher-ranked peers therefore receive greater weight in Panel C only. In addition to peer variables, models include rank and other controls as for Table 3. Dependent variables are also as for Table 3. Odd-numbered columns include only peer variables; even-numbered columns add indicator variables for each of the eight elite programs and a foreign-school indicator, with other US programs as the omitted category. The "High Tax School" and "Other elite eight" rows in even columns report enrollment-weighted averages of the individual school coefficients for the high-tax group (Harvard, MIT, Stanford, Princeton, Yale) and the other top-eight group (Chicago, Northwestern, Berkeley), respectively, where the weights are within-group enrollment shares; standard errors are computed via *lincom*. The table also reports a p-value testing the equality of the high-tax and other-elite school effects in each panel. The sample includes application cohorts before 2020. Standard errors are robust to heteroskedasticity. N = 2,582.

Table 6: Value-Added by School

	High Tax	WDI		Top 5		DI	All Econlit	Any Pub
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
MIT	✓	1.18***	0.71***	1.44***	0.89***	0.28*	0.14	0.05
		(0.16)	(0.20)	(0.20)	(0.25)	(0.15)	(0.15)	(0.06)
Harvard	✓	0.92***	0.68***	1.23***	0.94***	0.35***	0.20	0.02
		(0.16)	(0.18)	(0.21)	(0.22)	(0.13)	(0.12)	(0.05)
Stanford	✓	0.53***	0.42**	0.77***	0.62**	0.28*	0.14	0.03
		(0.20)	(0.20)	(0.25)	(0.26)	(0.15)	(0.14)	(0.06)
Princeton	✓	0.72***	0.69***	0.80***	0.74***	0.53***	0.41***	0.07
		(0.20)	(0.21)	(0.26)	(0.27)	(0.14)	(0.13)	(0.06)
Berkeley		0.56***	0.56***	0.67***	0.66***	0.36**	0.34**	0.18***
		(0.19)	(0.19)	(0.24)	(0.24)	(0.15)	(0.14)	(0.06)
Yale	✓	0.20	0.18	0.14	0.10	0.20	0.17	0.08
		(0.24)	(0.24)	(0.29)	(0.30)	(0.17)	(0.15)	(0.07)
Northwestern		0.54*	0.53*	0.45	0.42	0.23	0.07	0.06
		(0.29)	(0.28)	(0.38)	(0.38)	(0.19)	(0.16)	(0.08)
Chicago		0.39	0.37	0.68**	0.66**	0.15	0.11	0.07
		(0.25)	(0.26)	(0.32)	(0.32)	(0.16)	(0.14)	(0.07)
Foreign School		-0.27	-0.26	-0.37	-0.35	0.08	0.31	-0.02
		(0.24)	(0.24)	(0.33)	(0.33)	(0.23)	(0.29)	(0.09)
Rank/Admission Controls			✓		✓	✓	✓	✓
Dep. var. mean		0.45	0.45	0.66	0.66	2.99	4.43	0.63
p-value all 8 equal		0.000	0.330	0.000	0.116	0.505	0.410	0.187
p-value high-tax 5 equal		0.000	0.122	0.000	0.032	0.383	0.378	0.759
p-value high-tax ex Yale 4 equal		0.001	0.443	0.002	0.489	0.406	0.266	0.727

Notes: This table replicates results from versions of the Poisson models used for Table 3, replacing school-group indicators with individual school dummies. Other US schools remains the omitted category. The first column marks high-tax schools with a checkmark. Specifications and dependent variables are as for Table 3. The table reports four p-values testing equality of school coefficients: (i) all elite eight schools equal, (ii) the 5 high-tax schools (MIT, Harvard, Stanford, Princeton, Yale) equal, and (iii) the 4 high-tax schools excluding Yale equal. Standard errors are robust to heteroskedasticity. $N = 2{,}582$.

Table 7: Value-Added by School—Home Journal Outcomes

					With and Without Insider Journals			
	High Tax	QJE	JPE	AEA P&P	WDI	WDI ex 3	Top 5	Top 3
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
MIT	✓	1.52***	0.25	0.95***	0.71***	0.53***	0.89***	0.81***
		(0.37)	(0.38)	(0.27)	(0.20)	(0.19)	(0.25)	(0.26)
Harvard	✓	1.62***	0.64**	0.90***	0.68***	0.46***	0.94***	0.77***
		(0.33)	(0.32)	(0.24)	(0.18)	(0.17)	(0.22)	(0.23)
Stanford	✓	-0.12	0.36	0.64**	0.42**	0.47**	0.62**	0.77***
		(0.49)	(0.36)	(0.27)	(0.20)	(0.21)	(0.26)	(0.28)
Princeton	✓	1.00**	0.60	0.51	0.69***	0.65***	0.74***	0.71***
		(0.42)	(0.41)	(0.32)	(0.21)	(0.20)	(0.27)	(0.27)
Berkeley		0.82*	0.82**	0.72**	0.56***	0.42**	0.66***	0.58**
		(0.43)	(0.40)	(0.32)	(0.19)	(0.19)	(0.24)	(0.26)
Yale	✓	-0.39	0.69	-0.24	0.18	0.16	0.10	-0.04
		(0.66)	(0.44)	(0.37)	(0.24)	(0.26)	(0.30)	(0.35)
Northwestern		-0.26	1.06**	0.09	0.53*	0.47*	0.42	0.31
		(0.81)	(0.49)	(0.45)	(0.28)	(0.24)	(0.38)	(0.37)
Chicago		0.83*	0.81*	0.40	0.37	0.25	0.66**	0.57*
		(0.43)	(0.42)	(0.33)	(0.26)	(0.25)	(0.32)	(0.34)
Foreign School		-1.49	-0.39	-2.06**	-0.26	-0.17	-0.35	-0.19
		(1.03)	(0.65)	(1.02)	(0.24)	(0.24)	(0.33)	(0.37)
Dep. var. mean		0.14	0.09	0.18	0.45	0.32	0.66	0.43

Notes: Each column reports estimates from a Poisson regression model regressing productivity measures on school dummies, with the controls and sample used for Table 6. The first column marks high-tax schools with a checkmark. Columns (1)–(3) use as dependent variables publication counts in the QJE, JPE, and AEA Papers & Proceedings, respectively (AEA P&P is classified separately from the AER and is not part of the Top 5). Columns (4) and (6) repeat the WDI and Top 5 specifications from Table 6 for comparison, while column (5) uses WDI excluding QJE, JPE, and AEA P&P from the journal set, and column (7) uses top 3 publications (AER, Econometrica, and the Review of Economic Studies—i.e., the top 5 minus the QJE and JPE). Comparing columns (4) with (5) and (6) with (7) shows that school effects are not driven by publications in journals associated with specific schools. Robust standard errors in parentheses. $N = 2{,}582$.

Appendix

Table A1: Sensitivity to MIT Admission and NSF Controls

	WDI		Top 5		DI		All Econlit	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Tax School	0.56***	0.60***	0.72***	0.78***	0.34***	0.36***	0.22**	0.23**
	(0.15)	(0.15)	(0.20)	(0.20)	(0.11)	(0.10)	(0.10)	(0.10)
Other Elite	0.47***	0.49***	0.59***	0.61***	0.26**	0.27**	0.20*	0.20*
	(0.17)	(0.17)	(0.23)	(0.23)	(0.12)	(0.12)	(0.11)	(0.11)
Foreign School	-0.26	-0.26	-0.35	-0.35	0.08	0.08	0.31	0.31
	(0.24)	(0.24)	(0.33)	(0.33)	(0.23)	(0.23)	(0.29)	(0.29)
Admitted to MIT	0.16		0.22		0.08		0.04	
	(0.12)		(0.14)		(0.10)		(0.09)	
NSF Winner	0.13		0.10		0.10		0.07	
	(0.12)		(0.14)		(0.10)		(0.09)	
Dep. var. mean	0.45	0.45	0.66	0.66	2.99	2.99	4.43	4.43
p-value High Tax = Other Elite	0.528	0.412	0.434	0.314	0.372	0.303	0.799	0.738

Notes: This table examines sensitivity of tax-group value-added estimates to the inclusion of dummies for MIT admission and NSF awards as controls. All models include rank and other controls as for Table 3. Dependent variables are also as for Table 3. The sample includes application cohorts before 2020. Standard errors are robust to heteroskedasticity. $N = 2{,}582$.