Money isn't everything: Linking college choice to winning prizes and professorships

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ABSTRACT: We expand upon the literature that considers how characteristics of undergraduate schools affect non-income outcomes by considering Nobel Prize winners and full professors at Top 25 universities. We introduce National Merit Scholars as a percentage of 1960-61 class as a time-appropriate measure of student quality, and show how this measure largely matches up with prior expectations and observed outcomes. We conclude with discussion of the convex relation between National Merit Scholars and these professional outcomes.

Keywords: Returns to Education, College Quality, Human Capital

JEL codes: I2, J24

When considering the benefits of attending elite undergraduate schools, the economics literature has largely (and understandably) focused upon how school characteristics affect future income and wages.[1] We choose to consider non-pecuniary returns to elite education, by studying the winners of the Nobel Prize and those who became full professors at Top 25 universities. To our knowledge, Hamermesh and Pfann (2009) is the only other paper that considers Nobel prize winners, and it does so by considering the impact of post-doctoral achievements (e.g., citations of publications). Our proposed non-pecuniary outcomes speak to how characteristics of undergraduate education affect the likelihoods of attaining highly visible and prestigious achievements that do not coincide with material success.

[1] Long (2008) provides a thorough survey in addition to some reconciliation of the various positions, but see also Behrman *et al.* (1996), Black and Smith (2006), Brewer *et al.* (1999), Dale and Krueger (2002), Eide *et al.* (1998), Hoekstra (2009), and Lindahl and Regner (2005).

Our goal is to provide stylized facts that link undergraduate institutions to eventual success as measured by the above. We are especially interested in documenting convexity in these relationships. Such non-linearities may lend insight into separating out selection effects from value-added by educational institutions in future work.

Data

We consider two measures of our non-pecuniary outcomes: Nobel Prizes (through the 2007 awards) and full professorships at top 25 universities. Nobel Prizes are divided into two categories. The first (SCINOBEL) includes Chemistry, Economics, Physics, and Physiology/Medicine. The second (ALLNOBEL) encompasses the first but also includes Peace and Literature. We discard winners who graduated from universities outside of the U.S., and we make no distinction between solo-winners and group-winners. For full professorships (FULLPROF), we consider the faculty of eight departments (biology, chemistry, economics, English, history, mathematics, physics, and political science) at the top 25 universities in the 2007 *US News and World Reports* rankings.[2] We then used CVs to determine these individuals' *alma maters* and aggregated these outcomes by school.

Some schools structurally changed over the last fifty years, becoming coeducational by consolidating with sister schools. We treat such schools as if they were always a single institution. Student composition may also have changed, so we did not want to use only current school-SAT averages. Systematic information on SAT scores by university, however, is generally unavailable prior to the 1980s. We therefore worked with data collected by the National Merit Scholarship Corporation (NMSC), the non-profit organization that determines eligibility using the very similar PSAT. These data appear to have been largely overlooked by

[2] The full list of schools can be found in the Appendix, as can other criteria used for categorization.

economists, but their predictive power for life outcomes is consistent with Burton and Wang (2005), who linked GRE scores to grades in the first year of graduate school.

The first National Merit Scholars (NMS) entered college in 1956. The NMSC provided us with information on the total number of NMS attending a school over four distinct academic years (1956-57, 1960-61, 1965-66, and 1970-71). In the latter two school years, some schools began offering merit scholarships to students who had performed well on the PSAT but had not become NMS. We therefore consider only official NMS rather than including school-sponsored NMS as well. Furthermore, it appears that in 1965-66, some schools began aggressively targeting NMS for recruitment. There generally appears to be little strategic behavior among schools in the 1960-61 cross-section, and so we use that year's data in lieu of school-SAT average score.[3] We do this not to determine the causal impact of an additional NMS but rather to proxy for the general student quality of the era.

We are ultimately interested in how attendance at schools with certain characteristics affects the probability of our outcomes, and this necessitates determining the numbers of alumni. Numerous inquiries to various schools for alumni populations were unsuccessful, so we used class size from 2007 as our population measure. If schools have grown in equal proportion over the last five decades, this measure should be adequate. We then scale our aggregate dependent variables by this class size to create a "probability" of a school's alumnus securing the outcome.[4] Finally, early regressions suggested that inclusion of additional school characteristics may be helpful, especially in reducing the problem of heteroskedasticity. To this end, our last regressor

[3] Unreported results included current school-level information on recent SAT scores (average and 25%-75% range). Such variables only rarely achieved statistical significance and never approached the power of the NMS variables.
[4] As we cannot compute true *ex post* probabilities, we ask the reader's indulgence as we use "probability," "percentage," and "per-capita" to denote our available scaled version of these concepts.

is an indicator variable for whether a school is a member of the Ivy League (i.e., Brown, Columbia, Cornell, Dartmouth, Harvard, Penn, Princeton, and Yale).

We then construct three samples. The first sample includes only schools that have a graduate who won some sort of Nobel Prize (n=102). The second includes all schools that have a graduate who won some sort of Nobel Prize or is a full professor at a top university (n=421). We use this latter sample with Nobel Prize probabilities so that we can have some observations with an empirical probability of zero. The third sample includes only schools with a graduate who is a full professor at a top university (n=405). Table 1 displays summary statistics and correlations by sample. The predictive power of our regressors is foreshadowed by the simple correlations among the variables. Most notable is the consistent and quite sizable correlation ($\rho>0.8$) between the percentage of the 1960-61 class that was National Merit Scholars and the probability of achieving our outcomes for any of our samples.

How do our outcomes match up with pre-existing notions of university quality? Table 2 lists the twenty schools with the highest class-size-adjusted outcomes as well as raw outcomes. Caltech tops all lists, while Harvard and Swarthmore hold the second or third spots. Across all three outcomes, the top eight schools are unsurprising. Outside the top eight, schools outside the academic elite are more substantially represented among Nobel Prize winners than top university full professorships, perhaps due to the very small number of people who were so honored.

Results

As expected, heteroskedasticity is a substantial problem in our estimation. While we display least squares estimates, we also show weighted least squares (WLS) estimates. Our estimated standard errors then employ the White correction on top of the WLS.[5] Our baseline regression for each outcome and each sample includes per-student National Merit Scholars, class size, and an indicator for whether the school is one of the eight Ivy League members. Also shown for comparison are regression results that include all unique second-order polynomial interactions except the squared per-capita National Merit Scholars. To detect evidence of convexity, of course, we must estimate a specification that includes all unique second-order polynomial interactions.

We first consider the sample of schools in which at least one alum had won a Nobel Prize by 2007 (n=102). Table 3 displays results for both Nobel Prize outcomes. Students that attended schools with higher ratios of National Merit Scholars or smaller enrollment were more likely to win a Nobel Prize. Examining the full specifications, the coefficient on the square of per-student NMS is positive and significant, indicating a convex relationship between our measure of student quality and our outcomes. We also see that the outcome probability is decreasing in student population for 91 out of 102 schools in the sample. Furthermore, the estimated coefficients on the Ivy-dummy and its interactions are never significantly different from zero. Table 4 shows Nobel Prize outcome results when using the larger sample of the union of Nobel Prize-winning schools and full professor schools (n=426). The inclusion of observations for which the dependent variable is zero broadly improves the precision, but results involving NMS are otherwise comparable to the small sample.

The impact of the convexity of the probability relationship is illustrated with a few examples in Table 5. Consider four schools that had roughly similar class sizes in 2007 but very different numbers of National Merit Scholars in 1960-‘61: MIT, Rice, Wesleyan, and Holy

[5] See Cameron and Trivedi, *Microeconometrics*, 2005. We regress the log of squared residuals on the relevant set of variables to obtain our predicted covariance matrix of the disturbance. Given our relatively small sample sizes, simple White-corrected standard errors were too imprecise to draw any conclusions.

Cross. Using all coefficients regardless of statistical significance, we calculate the predicted impact of increased student quality that would have been consistent with generating an additional NMS and additional increase in (NMS/Size) by 0.01. We employ the estimates from the SCINOBELS in the enlarged sample because of their increased precision, but estimated marginal impacts are similar in the other cases.

To interpret these numbers, imagine that Rice in 1960-61 was a “better” university than it was and that it attracted one more NMS. Had it been that better school, its scaled SCINOBEL would have risen from 2.622 to 2.698 (by 0.076). Had it been sufficiently better that it attracted a NMS ratio of 0.0952 instead of the actual 0.0852 (consistent with 73 instead of 65 NMS in a class of 763), then its scaled SCINOBEL would have risen from 2.622 to 3.200 (by 0.578).

The estimated convexity is most apparent by simply contrasting the schools’ predicted impacts. Had MIT and Holy Cross both been better schools so that they each enrolled an additional NMS in 1960, the estimated impact on MIT’s probability of a scientific Nobel is almost twice as great as that on Holy Cross’s. In a world where MIT and Wesleyan were both better schools so that their NMS/Size ratios each increased by a percentage point, the impact on MIT’s probability of a SciNobel is over twice that of Wesleyan’s. Rice’s student quality as measured by the 1960-61 NMS puts it in the top 10 of our sample, and yet comparable increases in student quality for it and MIT end up yielding advantages for MIT that are still 20% or 65% greater than those for Rice.

Figure 1 shows the predicted level of SCINOBEL/Size for non-Ivies at various levels of NMS/Size, using Table 4’s estimates with and without the quadratic term $(\text{NMS/Size})^2$. The impact of the convexity begins near the NMS/Size threshold of 0.02 and rises thereafter.[6] When schools reach an NMS/Size ratio of 0.1, their SCINOBEL/Size is predicted to be a full point

[6] Schools with NMS/Size ratios near 0.02 are Barnard, Case Western, Duke, and Northwestern.

higher than that estimated when convexity on this margin is ignored.[7] At the upper levels of university quality, the estimated benefits in terms of enhanced outcomes are substantial.

Table 6 displays similar results for full professorships. While convexity in student quality is still significant, it is less critical than in any of the Nobel regressions. The other notable difference is that here the Ivy League variables and their interactions with a few other regressors are significant. While estimates on the probability of achieving full professorship are marginally significant for the Ivies, those that attracted more National Merit Scholars early (i.e., Harvard) tended to offer an even greater advantage.[8]

Discussion

We have compared school-level realization of two novel outcomes to those schools' student quality as measured by the National Merit Scholar data, and in so doing have found the stylized fact of a convex relationship between the two. This convexity is important for both outcomes but less so for full professorships than Nobel prizes. Such convexity may be generated if school sorting has larger impacts on students with higher innate abilities either through improved training or due to some local economies of scale. Further work with less aggregated data is warranted.

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[7] Besides Rice (0.085), schools with NMS/Size ratios near this threshold are Macalester (0.090) and Oberlin (0.084).

[8] The Ivies ordered by this measure are Harvard (0.169), Princeton (0.067), Yale (0.053), Dartmouth (0.023), Columbia (0.016), Brown (0.015), Cornell (0.015), and Penn (0.005).

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Appendix

Guidelines for inclusion as full professor:

1. Only full professors were counted. No adjuncts or associates.
2. Teaching professors were not included.
3. Research professors were included.
4. Emeritus professors were excluded.
5. Professors with joint appointments in two or more departments were counted in each department where they had a full professorship.

Top 25 University list: Princeton, Harvard, Yale, Caltech, Stanford, MIT, Penn, Duke, Dartmouth, Columbia, Chicago, Cornell, Washington (St. Louis), Northwestern, Brown, Johns Hopkins, Rice, Vanderbilt, Emory, Notre Dame, Carnegie Mellon, Berkeley, Georgetown, Virginia, and Michigan.

Table 1: Summary statistics

A. Only Nobel-Prize winning schools (n = 102)

	Mean	Median	StDev	Min	Max
Pr(SCI)*1000	1.98	0.76	3.80	0	32.41
Pr(ALL)*1000	2.33	1.48	3.83	0.10	32.41
NMS	18.77	5.50	38.51	0	284
Size	2537	1385	2680	216	9620
NMS/Size	0.020	0.004	0.049	0	0.375
Ivy?	0.078	0	0.270	0	1

<u>Correlation matrix</u>

	Pr(SCI)	Pr(ALL)	NMS	Size	NMS/Size	Ivy?
Pr(SCI)	1.00	0.97	0.45	-0.29	0.86	0.15
Pr(ALL)	0.97	1.00	0.45	-0.36	0.86	0.16
NMS	0.45	0.45	1.00	-0.06	0.69	0.41
Size	-0.29	-0.36	-0.06	1.00	-0.24	-0.08
NMS/Size	0.86	0.86	0.69	-0.24	1.00	0.15
Ivy?	0.15	0.16	0.41	-0.08	0.15	1.00

B. Nobel-Prize winning & full-prof schools (n = 421)

	Mean	Median	StDev	Min	Max
Pr(SCI)*1000	0.48	0	2.05	0	32.41
Pr(ALL)*1000	0.57	0	2.13	0	32.41
NMS	6.63	1	20.64	0	284
Size	2146	1085	2257	25	10330
NMS/Size	0.008	0.001	0.026	0	0.375
Ivy?	0.019	0	0.137	0	1

<u>Correlation matrix</u>

	Pr(SCI)	Pr(ALL)	NMS	Size	NMS/Size	Ivy?
Pr(SCI)	1.00	0.98	0.51	-0.12	0.83	0.24
Pr(ALL)	0.98	1.00	0.52	-0.14	0.82	0.25
NMS	0.51	0.52	1.00	0.00	0.72	0.44
Size	-0.12	-0.14	0.00	1.00	-0.16	-0.02
NMS/Size	0.83	0.82	0.72	-0.16	1.00	0.20
Ivy?	0.24	0.25	0.44	-0.02	0.20	1.00

C. Full-prof schools (n = 405)

	Mean	Median	StDev	Min	Max
Pr(Prof)*1000	7.39	2	21.15	0.10	268.52
NMS	6.83	1	21.02	0	284
Size	2184	1120	2276	25	10330
NMS/Size	0.008	0.001	0.027	0	0.375
Ivy?	0.020	0	0.139	0	1

<u>Correlation matrix</u>

	Pr(Prof)	NMS	Size	NMS/Size	Ivy?
Pr(Prof)	1.00	0.74	-0.18	0.91	0.39
NMS	0.74	1.00	0.00	0.72	0.44
Size	-0.18	0.00	1.00	-0.16	-0.03
NMS/Size	0.91	0.72	-0.16	1.00	0.20
Ivy?	0.39	0.44	-0.03	0.20	1.00

Table 2: Top 20 schools & outcomes

* scaled by 2007 class size and multiplied by 1000

	Sci Nobel			All Nobel			FullProf	
BA School	Scaled	Raw	**BA School**	Scaled	Raw	**BA School**	Scaled	Raw
California Institute of Technology (Caltech)	32.41	7	California Institute of Technology (Caltech)	32.41	7	California Institute of Technology (Caltech)	268.52	58
Swarthmore College	10.78	4	Harvard University	11.32	19	Harvard University	185.23	311
Harvard University	10.13	17	Swarthmore College	10.78	4	Swarthmore College	137.47	51
Amherst College	9.71	4	Amherst College	9.71	4	Massachusetts Institute of Technology (MIT)	116.28	120
University of Chicago	8.98	11	Columbia University	9.24	16	Princeton University	96.67	119
Massachusetts Institute of Technology (MIT)	8.72	9	University of Chicago	8.98	11	Yale University	86.53	115
Columbia University	8.67	15	Massachusetts Institute of Technology (MIT)	8.72	9	Amherst College	80.10	33
Yale University	5.27	7	Haverford College	6.85	2	Haverford College	71.92	21
Cooper Union	4.36	1	Yale University	6.02	8	University of Chicago	50.61	62
Manchester College (IN)	3.74	1	Hamilton College	4.49	2	Columbia University	46.22	80
City College of New York	3.49	9	Cooper Union	4.36	1	Oberlin College	44.88	32
Haverford College	3.42	1	Rockford College	4.07	1	Rice University	41.94	32
Earlham College	3.35	1	Manchester College (IN)	3.74	1	Reed College	40.98	15
Union College (KY)	3.33	1	City College of New York	3.49	9	Shimer College	40.00	1
Dartmouth College	2.88	3	Randolph-Macon Women's College	3.49	1	Carleton College	38.82	19
Case Western	2.87	3	Earlham College	3.35	1	Williams College	38.08	19
Oberlin College	2.81	2	Union College (KY)	3.33	1	Stanford University	37.87	64
Whitman College	2.76	1	Benedictine College	3.08	1	Harvey Mudd College	37.53	7
Juniata College	2.74	1	Marietta College	2.96	1	Wesleyan University	34.07	23
Berea College	2.64	1	Virginia Military Institute	2.90	1	Dartmouth College	31.70	33

Table 3: Probability of winning Nobel Prize, sample of Nobel schools (n = 102)
 * bolded point estimates significant at 95% level

DV	1 - SCI/Size			1 - SCI/Size			1 - SCI/Size			2 - ALL/Size			2 - ALL/Size			2 - ALL/Size		
	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e
Int	1.04	**1.05**	0.15	1.27	**1.54**	0.25	1.97	**1.63**	0.24	1.62	**1.68**	0.17	2.12	**2.24**	0.25	2.74	**2.13**	0.23
NMS/Size	64.50	**42.85**	11.41	84.81	**43.02**	12.49	21.45	24.51	22.11	63.96	**43.56**	12.40	83.92	**45.21**	10.20	27.43	30.38	21.58
$(NMS/Size)^2$	---	---		---	---		166.09	**150.44**	55.73	---	---		---	---		148.08	**133.00**	54.20
Size/1000	-0.13	**-0.11**	0.02	-0.22	**-0.40**	0.09	-0.54	**-0.44**	0.08	-0.23	**-0.19**	0.02	-0.57	**-0.73**	0.10	-0.86	**-0.64**	0.07
$(Size/1000)^2$	---	---		0.02	**0.03**	0.01	0.042	**0.032**	0.007	---	---		0.05	**0.07**	0.01	0.071	**0.051**	0.007
NMS/1000	---	---		-44.10	-4.268	8.218	-11.71	6.53	8.09	---	---		-46.38	-11.196	9.653	-17.50	3.88	8.89
Ivy?	0.20	1.00	0.99	-0.50	0.60	1.96	1.26	2.38	2.68	0.27	0.91	1.14	-1.20	0.66	2.75	0.37	1.86	2.88
Ivy*NMS/Sz	---	---		32.56	4.68	16.99	11.20	-16.18	14.51	---	---		44.40	25.67	13.59	25.36	-7.41	15.44
Ivy*Sz/1000	---	---		0.74	0.35	0.74	0.05	-0.54	0.77	---	---		1.01	0.17	0.77	0.40	-0.36	0.83
R^2	0.75	0.66		0.80	0.67		0.83	0.82		0.77	0.69		0.83	0.71		0.86	0.83	

Table 4: Probability of winning Noble Prize, sample of Nobel and full prof schools (n = 421)
 * bolded point estimates significant at 95% level

DV	1 - SCI/Size			1 - SCI/Size			1 - SCI/Size			2 - ALL/Size			2 - ALL/Size			2 - ALL/Size		
	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e
Int	-0.05	**0.12**	0.04	-0.08	**0.24**	0.07	0.28	**0.21**	0.06	0.07	**0.13**	0.04	0.08	**0.33**	0.08	0.40	**0.28**	0.07
NMS/Size	63.56	**43.10**	9.76	80.79	**24.91**	9.93	17.88	24.70	14.24	64.98	**54.17**	10.29	81.92	**33.69**	12.24	26.67	25.94	16.30
$(NMS/Size)^2$	---	---		---	---		180.84	**158.59**	35.99	---	---		---	---		158.83	**154.65**	41.02
Size/1000	0.014	-0.008	0.01	0.09	**-0.09**	0.04	-0.08	**-0.07**	0.02	-0.007	-0.009	0.005	0.015	**-0.12**	0.04	-0.13	**-0.10**	0.03
$(Size/1000)^2$	---	---		-0.005	0.008	0.005	0.01	**0.006**	0.002	---	---		0.002	**0.011**	0.004	0.01	**0.009**	0.003
NMS/1000	---	---		-34.85	11.21	9.15	-1.36	8.03	5.49	---	---		-35.57	6.53	6.26	-6.16	8.24	6.19
Ivy?	1.07	1.73	1.08	1.13	2.23	2.09	3.32	4.25	2.83	1.38	1.65	1.02	1.07	2.39	2.61	3.00	4.26	3.03
Ivy*NMS/Sz	---	---		20.94	-2.71	19.78	-5.41	-21.29	11.64	---	---		28.08	8.34	15.14	4.95	-15.69	12.28
Ivy*Sz/1000	---	---		0.36	-0.21	0.71	-0.48	-0.99	0.80	---	---		0.42	-0.37	0.76	-0.31	-0.96	0.86
R^2	0.69	0.62		0.72	0.49		0.78	0.77		0.68	0.66		0.71	0.56		0.75	0.74	

- b_{OLS} denotes least squares point estimates, b_{WLS} denotes weighed least squares where weights taken from predictions from regression of ln(e2) on applicable regressors.
 Estimated standard errors reflect White-correction for heteroskedasticity using WLS point estimates.

Table 5: Predicted effects on SCINOBEL of quality increase consistent with higher NMS

	(1)	(2)	(3)	(4)
	2007 Class Size	1960-61 NMS	dPr(SCI) / dNMS	0.01* dPr(SCI) / d(NMS/Size)
MIT	1032	205	0.093	0.96
Rice	763	65	0.076	0.58
Wesleyan	675	32	0.067	0.45
Holy Cross	704	8	0.048	0.34

- estimated impacts taken from full specification of SCINOBELS in Table 4
- Col. (3) is differential impact of increasing NMS, (4) of increasing (NMS/Size)

Table 6: Probability of becoming full professor at elite university, sample of full prof schools (n = 405)

* bolded point estimates significant at 95% level

DV	FullProf/Size			FullProf/Size			FullProf/Size		
	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e	b_{OLS}	b_{WLS}	s.e
Int	2.19	**2.24**	0.27	3.15	**3.28**	0.39	3.97	**3.32**	0.36
NMS/Size	685.75	**600.72**	61.36	709.80	**530.34**	86.71	572.70	**440.03**	94.08
$(NMS/Size)^2$	---	---		---	---		393.47	**675.28**	231.85
Size/1000	-0.31	**-0.21**	0.04	-0.98	**-1.03**	0.17	-1.35	**-0.99**	0.15
$(Size/1000)^2$	---	---		0.10	**0.09**	0.02	0.13	**0.08**	0.02
NMS/1000	---	---		-121.99	38.00	50.65	-49.16	67.18	50.25
Ivy?	32.16	**21.50**	3.81	15.19	**20.80**	10.11	19.94	19.57	10.02
Ivy*NMS/Sz	---	---		513.09	**401.23**	81.98	456.04	**326.07**	69.33
Ivy*Sz/1000	---	---		0.63	-1.98	2.95	-1.18	-1.51	2.94
R^2	0.88	0.86		0.90	0.88		0.90	0.90	

- b_{OLS} denotes least squares point estimates, b_{WLS} denotes weighed least squares where weights taken from predictions from regression of $\ln(e^2)$ on applicable regressors. Estimated standard errors reflect White-correction for heteroskedasticity using WLS point estimates.

Figure 1: Impact of estimated convexity on Science Nobels