Engineering Salary Modeling and Analysis

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Abstract – Engineering salaries vary greatly by academic major, field of practice, and depth of expertise. This paper analyzes salary profile data abstracted from the Payscale.com database, the world's largest database of self-reported incomes (that contains ~8% of the salary data for all U.S. engineers). A non-linear model is developed that models the trajectory of the salary profile as a function of time with three parameters: 1) the base salary at the onset of engineering work, 2) the annual rate of salary increase, and 3) the rate of salary decay. The resulting model has a high degree of correlation, such that the standard error of the model is much less than the standard deviation of the observed engineering salaries. The derived salary profile models are then used to evaluate the net present value (NPV) of engineering graduates from the 150 top-ranked engineering colleges. The NPV and model coefficients are then regressed against the graduate's college ranking and entry SAT scores. The results follow expectations, namely that improved college rankings and SAT scores correlate with higher net present values of career earnings of $1,960 per ranking point and $849 per SAT point. The models have also been used to evaluate internal rates of return on engineering education

Keywords: Human capital; internal rate of return; engineering education; college rankings; salary profiles.

INTRODUCTION

This paper concerns the high fidelity modeling of salary profiles with the goal of characterizing the determinants of lifetime earnings and thereby providing guidance as to allocation of human capital. The issue of allocation of human capital is of critical concern at the individual, institutional, societal, and global levels. For an individual and his/her family, decisions must be made regarding how to invest in their education relative to potential economic and other intangible returns. The decision to pursue alternative majors at increasing levels of higher education will introduce the possibility of pursuing new career options albeit at the loss of other unknowable professional and personal opportunities. Accordingly, the individual believes that they are making rational decisions about their choice of major and enrollment in a specific educational institution based on personal interests and/or expected economic returns of their investment of time and money. Prospective populations may include traditional students and, increasingly, returning students seeking to reinvest in their education.

At the institutional level, administrations seek to develop and offer programs that will attract the highest quality students who will pay the highest bearable tuition, perform to the highest levels, earn the highest salaries and recognitions, and thereby provide the greatest return to the institution. Institutions often perform an economic analysis regarding the allocation of their investments in human capital, especially the number and classification of faculty lines across departments. Administrations must also reason about staffing, facilities, and policies that will impact their constituents' future success; potential determinants of success may include class sizes, instructor quality, internship availability, research experiences, extracurricular activities, academic counseling, professional placement, and others.

At the societal level, the apportionment of tax revenues to public education is a long tradition of democratic societies by which governments seek to develop human capital to induce productive work, promote social stability, and advance the quality of life. In the United States, individual states have primary authority over their public educational systems. Here, legislatures also perform economic analysis regarding the needs of their constituents and

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the allocation of resources across educational institutions. At the federal level, Congress seeks to provide guidance to state legislatures through incentives and related policies offered through the U.S. Department of Education (DoED). Furthermore, state and federal governments have a significant impact on public and private education through directed program development and technology research grants. Some recent examples of federal investment include initiatives in science, technology, engineering, and mathematics (STEM) programs, info/nano/bio technology research, and more recently advanced manufacturing. Once again, government agents are explicitly or implicitly performing economic calculus to justify budget allocations.

At the global level, ethicists suggest the need to consider a just society that recognizes the dignity of every human being towards the allocation of resources to encourage labor equality and solidarity. This concept of "social justice" suggests a very different allocation of resources across societies. The reason for the different suggested allocation of resources is that rates of return on investments in education decrease on the margin, meaning that rates of return decrease with increasing levels of education and salary. Accordingly, global economic analyses [1-3] suggest that global resources are more equitably distributed through the offering of lower levels of education in poor countries rather than higher levels of education in rich countries. While some engineers may view such lines of inquiry as provocative, theories about the investment and depreciation of human capital have become well developed and can provide useful guidance regarding the economic value of engineering education.

It is the long term goal of this work to quantitatively evaluate the economic value added of engineering education. As a first step to this analysis, the salary profiles of baccalaureate engineers from the top ranked 150 engineering colleges are modeled as a function of time. Later papers will apply the theory of human capital by considering the educational costs and career salary profiles of graduating engineers. The resulting analysis will be used to evaluate elasticity of investments in human capital at increasing levels of education, assess rates of return from individual and societal perspectives, guide career strategies for reinvestment in human capital, evaluate the dynamics of alternative engineering careers with respect to labor supply/demand and human capital depreciation, characterize the sensitivity of rates of return relative to student ability, and ultimately suggest the determinants of a "quality" engineering education.

LITERATURE REVIEW

The analysis of human capital has long been of interest to economists. With respect to the division of labor, Adam Smith [4] implied the existence of monetary value in human capital: "The acquisition of talents, by the maintenance of the acquirer during his education, study, or apprenticeship, always costs a real expense, which is a capital fixed and realized, as it were, in his person." Pigou also suggested the importance of human capital with regard to trade-offs in its development [5]: "There is such a thing as investment in human capital as well as investment in material capital."

The theory of human capital was more fully developed by various contributors [6-8]. By 1964, Becker's Human Capital examined marginal rates of return on education by comparing additional output relative to investment levels in human capital [9]. Becker recognized that while human capital is substitutable with respect to development and utilization, it is not transferable like other assets such as land, labor, or fixed capital. Some early, explicit assessments of the economic value added of education include the justification of executive compensation [10] and the value of military experience by examination of World War II veterans [11]. By 1976, many such studies (including value of engineering courses) had been conducted as reviewed by Blaug in a meta-analysis [12].

As set forth by Mincer [8, 13-15], the basic earning function allows the estimation of rate of return through the fitting of a semi-log function using the logarithm of earnings as the dependent variable. Mincer used two forms of the earning function, parabolic and Gompertz. The gross annual earnings $E_{s,t}$ for a worker with s years of schooling and t years of experience is expressed with parabolic dependence as:

$$\ln E_{s,t} = \ln E_0 + r_s s + r_p k_0 t - \frac{r_p k_0}{2T} t^2 \quad (1)$$

where r_s and r_p are the rates of return on schooling and post-school investments, k_0 is the ratio of investment to gross earnings at the start of work experience, and T is the positive net investment period (career work span). The Gompertz earning function incorporates a sigmoidal transfer function to express the decline in value of up-front investment in education:

$$\ln E_{s,t} = \ln E_0 + r_s s + r_p k_0 t + \frac{r_p k_0}{\beta}(1 - \exp\{\beta t\}) \quad (2)$$

where β is the annual decline of the ratio k_0. Mincer used these functions to evaluate the rates of return on different investments in human capital, and thereby gain understanding of the earnings structure as a function of schooling and age. Mincer found very low correlation coefficients across broad populations, with approximately 30% of the observed behavior typically explained. A primary finding is that increased earnings are correlated with self-investment activities after the completion of formal schooling, though dollar profiles of earnings will tend to "fan out" later in life given increasing variances in self-investment.

There are some major assumptions in these earning models. Perhaps most significant is the assumption of constant rates of return across the span of a career. The theory thus fails to explicitly model salary dynamics related to varying levels labor supply and demand due to global recessions, offshoring trends, or technological obsolescence. In theory, it would be possible to develop an expanded salary model but the procurement of the requisite historical and broad salary data is difficult in practice. A second significant assumption is that these salary models do not explicitly model the intellectual ability, emotional commitment, or educational quality at the individual level. Again, the influence of some of these determinants on the career earnings and value added of engineering education may be studied, but is not the primary focus of the current work.

ANALYSIS METHODOLOGY

Salary Data

Salary data was derived from the world's largest database of individual employee compensation profiles. Each compensation profile is provided by individuals motivated to gain access to peer salary comparisons for negotiation purposes. The database contains profile data for about 5% of the working population, though the proportion is higher in some (especially technical) disciplines. To avoid inadvertent disclosure of individual information in conflict with implemented privacy policies, a statistical abstract of salary data was analyzed. Here, population "buckets" were developed for working engineers according to degree level (from Associates to Doctoral), majors (14 most prevalent), engineering college (475 institutions), and year of graduation (six ranges including 1977-1986, 1987-1991, 1992-1996, 1997-2001, 2002-2006, 2007-2011). The top and bottom 0.5% of salaried earners were removed to reduce the likelihood of outliers; buckets exhibiting a coefficient of variation (σ/μ) greater than 100% were also discarded. The resulting database incorporated data for 75,036 individuals distributed across 11,149 unique buckets.

Table 1: Comparison of reported engineering salaries

	Median Salaries		Population			IRR
	US BLS	Payscale	US BLS	Payscale	%	%
Aerospace	$ 92,520	$ 70,442	71,600	2,677	3.7%	5.6%
Biomedical	$ 77,400	$ 76,470	16,000	6,472	40.5%	5.7%
Chemical	$ 84,680	$ 77,852	31,700	11,567	36.5%	6.6%
Civil	$ 74,600	$ 61,009	278,400	9,520	3.4%	5.0%
Computer	$ 97,400	$ 77,200	74,700	10,505	14.1%	6.3%
Electrical	$ 82,160	$ 79,203	157,800	13,834	8.8%	5.9%
Environmental	$ 74,200	$ 59,450	54,300	507	0.9%	6.1%
Industrial	$ 73,820	$ 70,635	214,800	4,345	2.0%	5.8%
Mechanical	$ 74,920	$ 68,677	238,700	20,302	8.5%	5.5%
Nuclear	$ 97,080	$ 92,695	16,900	865	5.1%	9.1%
All	$ 84,879	$ 72,500	1,571,900	75,036	4.8%	5.9%

A summary of the incorporated PayScale data is presented in Table 1 alongside data from the U.S. Bureau of Labor Statistics (USBLS) for validation purposes. It is observed that the size of the surveyed population used for this study relative to the USBLS varies significantly by engineering major, from 0.9% of environmental engineers to 40.5% of biomedical engineers. While the variances are interesting, the most important variance may be the upward bias in the median salaries reported by the USBLS. There are several possible explanations for this bias, the most likely of which is that the self-reported salary profiles incorporated in this study are from more recent graduates who tend to have lower salaries than engineers with greater experience. This skewed distribution of salary profiles is not problematic since the presented analysis explicitly models salary growth as a function of experience to evaluate the economic value added of engineering education.

There are, of course, issues of self-selection that may inadvertently alter the distribution of engineering salaries incorporated into the presented analysis and results. For example, engineers having left the field (such as homeless veterans) would likely not participate in the salary survey. Conversely, highly satisfied engineers with stable employment also would be less likely to participate in the salary survey. Still, the advantage of the incorporated database relative to the USBLS, ASEE, and other professional/institutional sources is that the incorporated data provides an objective view of the salaries along with degree characteristics across a large and diverse population.

Evaluation

The subsequent analysis is restricted solely to recipients of bachelor's degrees of engineering. In evaluating the economic value of engineering education, it is important to develop a high fidelity model that provides an accurate representation of the evolution of engineering salaries as a function of experience. Furthermore, it is desirable that the developed model has a minimum number of coefficients and that those coefficients have a readily understandable meaning. As such, the following model was developed for salary, *s*, as a function of time, *t*, with a Gompertz type sigmoidal behavior:

$$s(t) = b(1+r)^{t\cdot exp(t/\tau)} \tag{3}$$

where *b* is the base salary at the onset of engineering work, *r* is the annual rate of salary increase, *t* is the number of years of work experience, and τ is the rate of decay. The model coefficients were fitted using the Matlab function fminsearch to minimize the objective function, *f*, representing the sum of squared error between the salary predictions and salary observations:

$$f = \sum\left(\left(s_{pre} - s_{obs}\right)^2/n\right)^{1/2} \tag{4}$$

where s_{pre} is the predicted salary, s_{obs} is the observed salary, and *n* is the number of observations within a population bucket. The model was found to fit a very broad variety of observed behaviors including non-monotonic functions having low τ. These models can then be used to assess the net present value and internal rate of return as discussed in the next section.

RESULTS AND DISCUSSION

Figure 1 plots the aggregate annual salary profile as a function of years of experience for all 38,572 bachelor degreed engineers from the top-ranked 150 engineering schools incorporated in the study. The data points represent the mean salaries of all engineers as grouped into buckets with varying years of experiences as previously defined; the vertical error bars represent one standard deviation of salaries. The thick dashed line in the figure represents the model of equation (3) with *b* equal to 44929, *r* equal to 8.9%, and τ equal to 32.5 years. It is observed that the standard error of the model (deviation between thick line and data points) is much lower than the standard deviation of the salaries represented by the error bars.

The large variations in salaries are driven by a number of factors including type of engineering major, cost of living due to geographic disparities, years of experience within a population bucket, differences in work responsibilities, perceived quality of the engineer, negotiation capabilities, and others; the role of some of these determinants will be investigated in this and other papers. Salaries tend to increase with increasing years of experience and “fan out” as found by Mincer [8] who suggests that the widening of the salary distribution is related to self-investment in one’s human capital. Analysis of many salary profiles supports this premise, but the behavior of salary profiles varies widely between different majors and institutions as later investigated. Somewhat counter intuitively, this fanning out of the salary profile has a reduced economic impact given the long time horizon and deep discounts to the present value associated with the time value of money.

Salary profiles were provided for each aggregate population of the top-ranked 150 engineering colleges. The statistics for the model parameters were analyzed; Figure 2 plots the median salary profile of baccalaureate engineers with the model parameters perturbed by one standard deviation. For each of the model parameters, an increase in the parameter value results in higher career salaries albeit in different manners. The parameter *b* corresponds directly to an increase in the starting salary at time *t* equal to 0, such that an increase in *b* linearly scales the entire salary profile. The parameter *r* corresponds to the initial rate of salary, year over year, such that an increase in *r* would exponentially increase the salary profile in later years. However, the future salaries are tempered by obsolescence, modeled here by the Gompertz type function with rate of decay τ. Increases in τ will tend to postpone the eventual decay of salaries. In Figure 2, it may appear that the effect of r and τ are similar, but the two parameters with respect to their effect of the model topology.

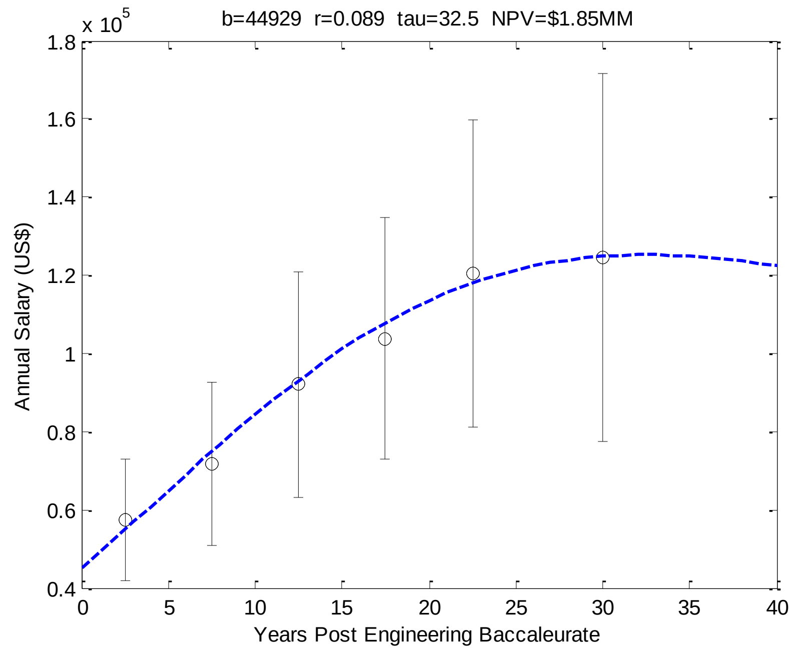

Figure 1: Projected salary profile for the aggregate of bachelor degreed engineers

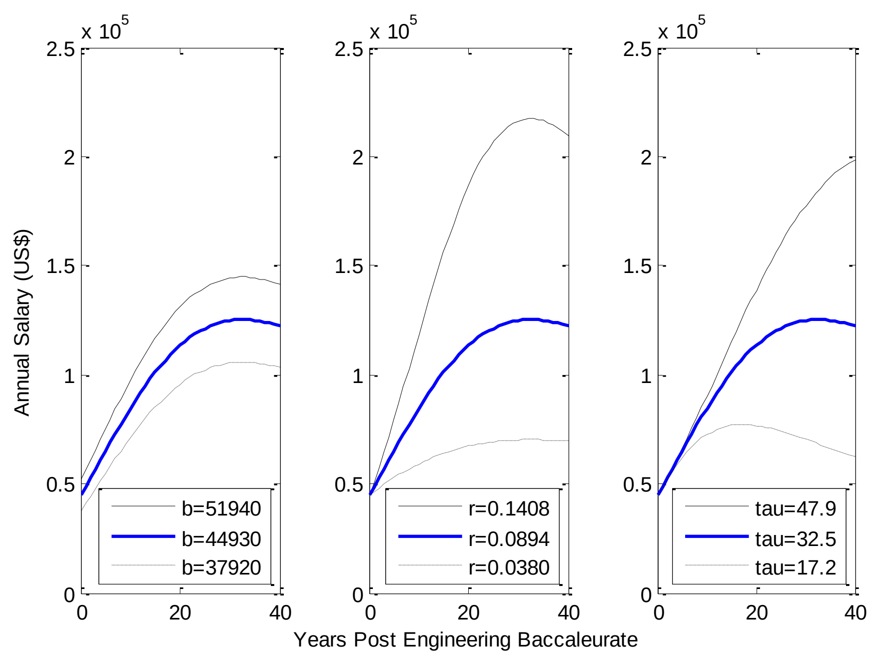

Figure 2: Projected salary profile for the aggregate of bachelor degreed engineers

The correlation, $R(i,j)$ between the model parameters was determined from the between the model parameters (b, r, and t) was determined from the 150 salary models, with the result provided in Eq. (5). The maximum p-value across the correlations was 1e-9, indicating that the correlations were highly statistically significant. The correlation between b and r of -0.799 indicates that a high starting salary actually results in a lower year over year raises. In retrospect, this result may be expected since free market pressures will tend to drive post-baccalaureate earnings to a common value. The correlation between b and τ is somewhat surprising, since it indicates that a high starting salary and a slow rate of decay are coupled. The premise here is that high quality engineering education can produce graduates that are in demand from the onset until the completion of their careers. Lastly, the correlation between r and τ is likely related to the confounding of the two parameters with regard to profile topology.

$$Corr\left(\begin{bmatrix} b \\ r \\ \tau \end{bmatrix}, \begin{bmatrix} b \\ r \\ \tau \end{bmatrix}\right) = \begin{bmatrix} 1.000 & -0.799 & 0.548 \\ -0.799 & 1.000 & -0.636 \\ 0.548 & -0.636 & 1.000 \end{bmatrix} \tag{5}$$

Consider the net present value (*NPV*) of the lifetime salary calculated assuming a forty year engineering career span as:

$$NPV = \sum_{t=1}^{40} \frac{s(t)}{(1+i)^t} \tag{6}$$

For the aggregate salary profile plotted in Figure 1 for bachelor degreed engineers, the *NPV* is $1,854,000 assuming a cost of capital, *i*, of 4.1% per year (the present average national fixed rate for a thirty year mortgage). The sensitivity of the net present value was evaluated by perturbing the salary model coefficients as plotted in Figure 2. Table 2 provides the results. It is observed that all model parameters have a significant impact on the net present value. The right hand column of Table 2 reports the sensitivity of the NPV to changes in the model parameters, as measured by how one standard deviation change in the model parameters changes the number of standard deviations in the NPV across the top ranked engineering colleges.

Table 1: Relationship between model parameters and net present value of salary profile

Parameter	*Change in NPV*	$\sigma_{NPV}/\sigma_{\{b,r,\tau\}}$
b, base salary ($, year 0)	41.3$ per 1$ in b	1.46
r, rate of increase (%/year)	153,000$ per 1% change in r	3.97
τ, decay (years)	28,400$ per 1 year change in τ	2.20

It is of interest to understand how characteristics of engineering education relate to these model parameters, and this is a focus of on-going research. As a first step, consider the impact of the two most common two measures of quality: 1) US News & World Report College Ranking, and 2) average SAT scores of incoming students. Figure 3 verifies the expected salary behavior, namely that 1) NPV increases with improved college rankings, and 2) NPV increases with SAT performance. The values of the coefficients are interesting to consider: $1,960 in NPV per ranking and $850 per SAT point.

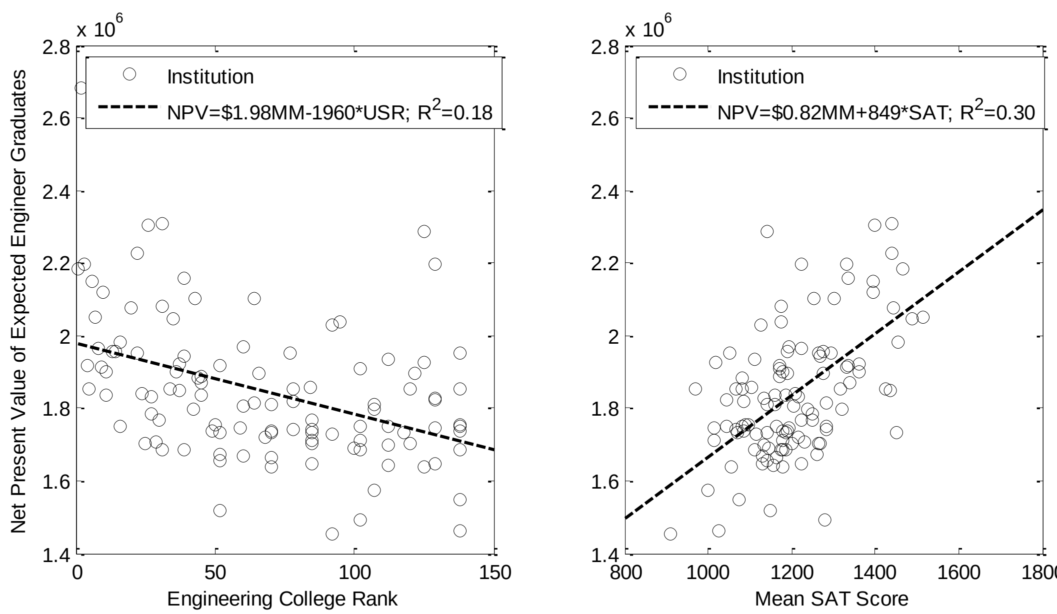

Figure 3: Projected net present value of career salaries as a function of rank and SAT scores

While there is a significant amount of scatter in the data of Figure 3, Mincer also reported that approximately 30% of the observed behavior was typically explained. The source of the low correlation is due to the high variance in individual student's future earnings as observable by the standard deviations in the salary observations plotted in Figure 1. As a first step in investigating the causal linkages between the determinants (ranking and SAT score) and the NPV, it may be useful to consider the effect of these determinants and the model parameters for starting salary, *b*, year over year rise in salary, *r*, and rate of salary decay, τ. These regressions are next plotted in Figure 4 to 6.

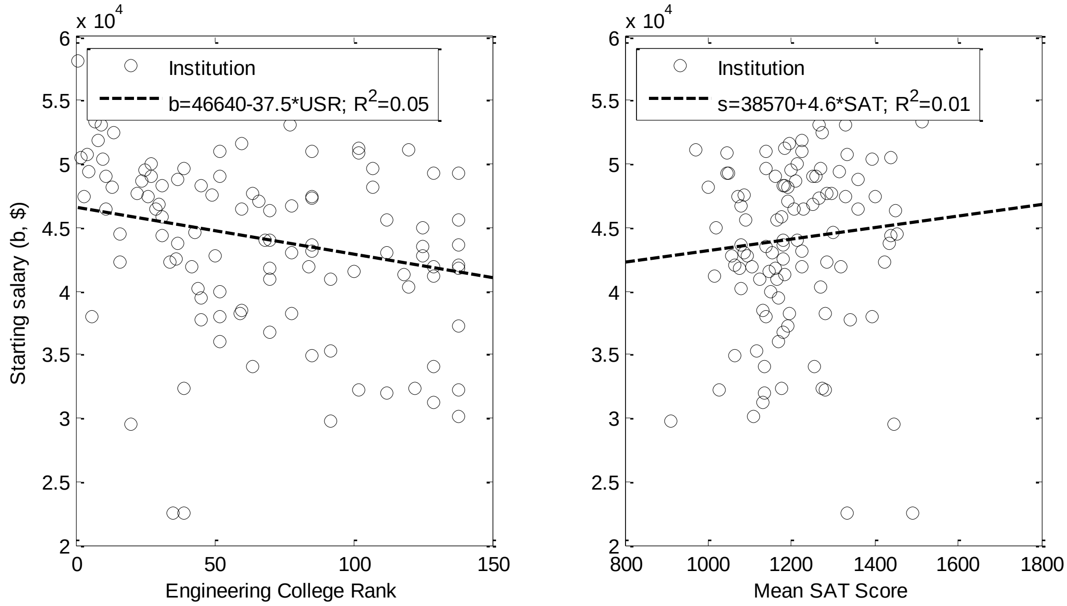

Figure 4: Starting career salaries as a function of college ranking and student SAT scores

Figure 4 indicates that the starting salary has a very weak correlation with college ranking and student SAT scores. While the correlation is very weak, it is interesting to verify that the statistics for the model parameters presented in Figure 4 do translate to the behaviors presented in Figure 3. For example, the coefficient of starting salary is $37.5 per reduction in school ranking. However, each dollar change in starting salary leads to $41.3 increase in NPV as reported in Table 2. Multiplying these together coefficients together contributes $1,549 in NPV per point of ranking, which is a large proportion of the $1,960 coefficient presented in Figure 3.

The sensitivity of the coefficient for year over year salary increases, *r*, is plotted in Figure 5. As might be expected, the model indicates that salary increases are positively correlated with SAT score: a 100 point increase in SAT score loosely correlated to a 0.86% increase in *r* or a $131,580 change in the NPV of lifetime salary. Perhaps more interesting is the loose but negative correlation of *r* with college ranking, which indicates that graduates of lesser ranked colleges tend to have a higher raises then similar graduates from better ranked schools. The hypothesis here is that graduates from more poorly ranked institutions have a lower starting salary and, as such, there is greater freedom for future salary increases in the free market for their salaries to catch up. Conversely, the fact that graduates of more highly ranked schools does not have a higher rate of raises is indicative that their education does not command sustained larger increases in future salaries.

Figure 6 plots the regression for the rate of salary decay, τ, as a function of school ranking and student SAT scores; lower values of τ correlate to faster reductions in future salaries and so reduced NPVs. The results presented in Figure 6 are surprising inasmuch as they suggest the rate of decay decreases with improved college rankings and student SAT scores. While it is possible that there are causal reasons for these relationships, it is more likely that the non-linear relationships between *b*, *r*, and τ in equation (3) are confounding or dominating the true relationships.

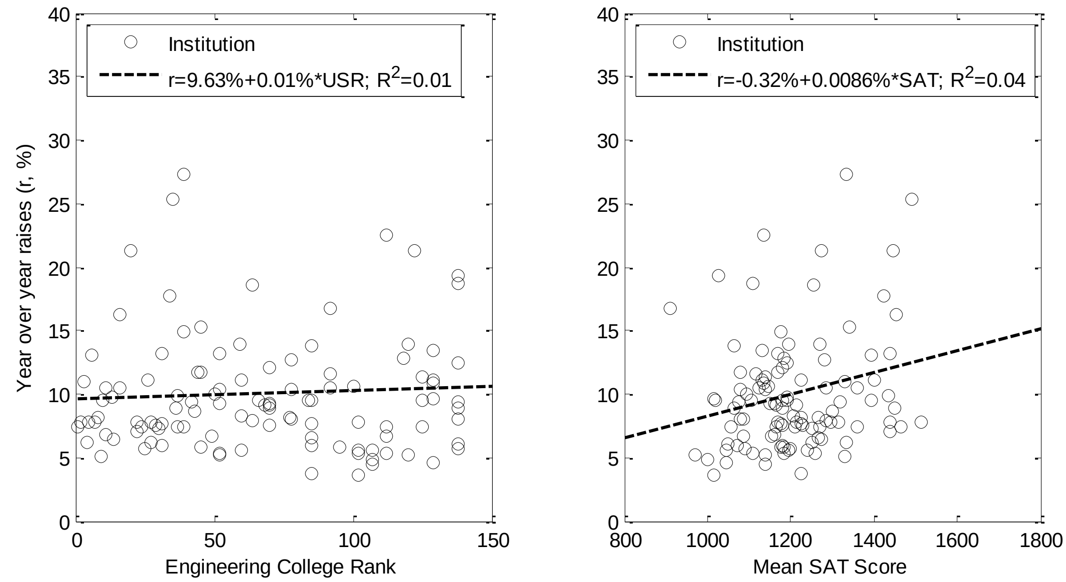

Figure 5: Annual rate of salary increases as a function of college ranking and student SAT scores

The empirical model of equation (3) provides an excellent fit to the observed salary profiles without the standard error ever exceeding the observed standard deviation across 70,000 salary profiles, 180 engineering colleges, and 15 different majors. However, the high value of τ (~35 years), low correlation coefficients (~0.02), and unexpected behavior (opposite to what might be expected) suggests that this coefficient could be deleted or the model topology otherwise modified to provide improved understanding. Accordingly, further analysis is planned in which: 1) the IPEDS data will be updated and expanded, 2) additional models for salary functions will be analyzed, 3) sensitivity of salary NPV and model coefficients will be analyzed with multiple regression.

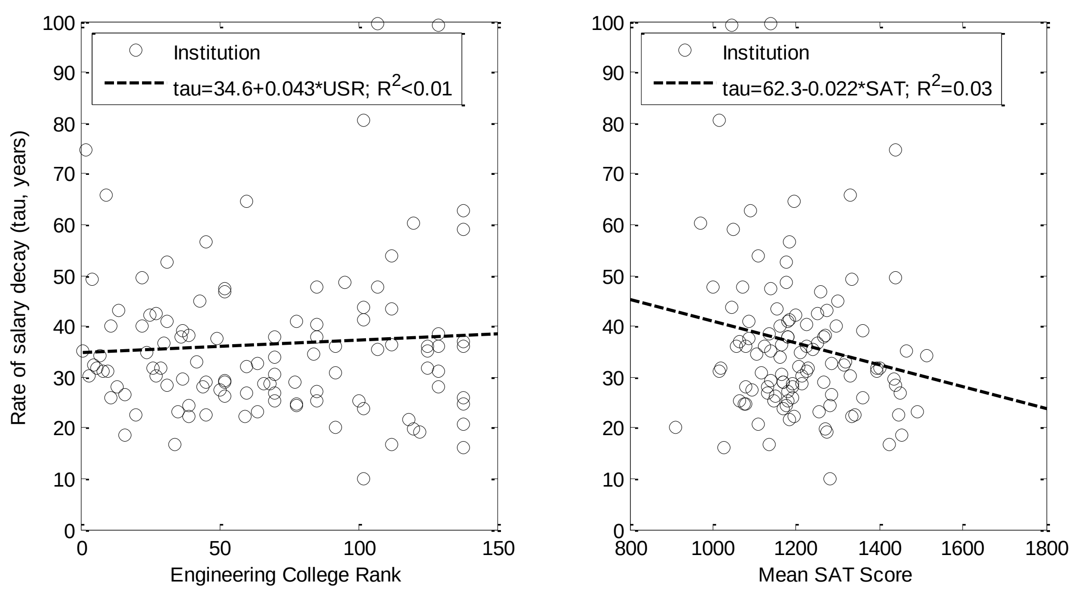

Figure 6: Rate of salary decay as a function of college ranking and student SAT scores

CONCLUSIONS

This study was intended to lay the groundwork for further analysis. While not analyzed herein, a primary conclusion is that rates of return for engineering education (now on the order of 6 to 10%) have declined significantly from Psacharopoulos' study in 1972 (then on the order of 19%). This decline is due to the reduction in engineering salaries relative to the increasing costs of engineering education. A continued downward trend in the rate of return for engineering education is not sustainable in the long term. Indeed, if engineering has the highest or one of the highest rates of return compared to other degrees and profession, then there is almost certainly a "bubble" in higher education as characterized by the point at which the internal rate of return falls below the inflation rate. Especially troubling is that these results model the "private" rates of return as observed by the student. By comparison, the "public" rates of return would include the true cost of education including subsidies, grants, infrastructure, etc. and so would be necessarily much lower.

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