University Startups and Entrepreneurship: New Data, New Results

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Abstract: This paper empirically examines university entrepreneurship by commercialization of faculty inventions through startup firms from 1994 through 2008. Using updated data from the Association of University Technology Managers (AUTM) and from the 2010 NRC doctoral program rankings, our research reveals several findings. First, we find that university entrepreneurship is more common in bad economic times. As NASDAQ returns decrease, the number of university startups increases, suggesting that entrepreneurship can be a vital component of economic recovery. Second, we find a structural difference in how university startups are created after the year 2000. The quality of the engineering department and the size of the biological sciences department are more important after the NASDAQ stock market crash. These two findings suggest that venture capitalists are now more selective about where they invest their capital and that bioscience startups require significantly more resources to be successful. Third, the updated 2010 NRC doctoral program rankings reveal that the quality of a biological sciences department, when measured by scholarly research output, is positively associated with the creation of startup companies. Finally, conditional on creating at least one startup, each additional employee in a TTO will significantly increase the rate of university startups.

(JEL I23, M13, O31)

I. Introduction

Since the passage of the Bayh-Dole Act in 1980, more than 5000 companies have been formed from university research projects.[1] This legislation, which allows universities to retain ownership and commercialize inventions generated from federally-funded research, has revolutionized university entrepreneurship. While the Act allows all universities an equal opportunity for research commercialization, some universities have reaped substantially larger financial gains compared to other universities. In 2009 alone, MIT received over 75 million dollars in income through its technology transfer office (TTO).[2] By working with staff to identify and develop their ideas, the university TTO is an important component of successful research commercialization. With millions of potential dollars at stake, a deeper understanding of other factors that influence commercial success of university research ideas is worth undertaking.

Earlier research has shown that faculty quality, federal funding, and invention disclosures are significant predictors of university startups. This paper builds upon these findings in several ways. First, we use additional data through 2008 and analyze a number of potential new predictors of university entrepreneurship. We look inside the "black box" and analyze how graduate program size, faculty research productivity, TTO size, and other variables within a university's control affect entrepreneurship. We utilize the 2010 National Research Council (NRC) doctoral program rankings to generate updated measures of department quality and size. In addition to the number of initiated startups, we also examine the number of startups generated within the university's home state. Second, the additional years of observations allows us to test for a structural break in the data. If a

[1] http://www.newswise.com/articles/thirty-years-after-passage-bayh-dole-act-drives-the-economy-protects-public-health.

[2] http://web.mit.edu/tlo/www/about/office_statistics.html

structural break exists, factors which were important in the past may no longer be important today. We also examine an additional econometric specification, the hurdle model, to better estimate the parameters driving entrepreneurial activity.

The data to answer these new lines of inquiry is collected from several sources. AUTM (Association of University Technology Managers) conducts an annual licensing survey of universities and provides a single resource for information on licensing activity and income, TTO size, startups, and other outcomes of interest. Our research includes data through 2008, the latest year of available data at the time of writing. The NVCA (National Venture Capital Association) provides venture capital funding levels by region and state. The final dataset come from the Department of Education. IPEDS (Integrated Postsecondary Education Data System) releases information on the size of a university's graduate program.

From these sources, we assemble a dataset of U.S. universities from 1994 to 2008. We use a negative binomial model for many of our regressions because of the count nature of the data. We also provide results using a hurdle model due to the non-trivial number of zero university startups. Whenever a significant threshold must be overcome for the dependent variable to have a positive value, hurdle models may better reflect the underlying description of the data. In the case of university entrepreneurship, significant resources must be expended to generate the first successful startup.

Our research reveals several findings. First, we find that university entrepreneurship is more common in bad economic times. As NASDAQ returns decrease, the number of university startups increases, suggesting that entrepreneurship can be a vital component of economic recovery. Second, we find a structural difference in how university startups are created after the year 2000. The quality of the engineering department and the size of the biological sciences department are more important after the NASDAQ stock market crash. These two findings suggest that venture capitalists are now more selective about where they invest their capital and that bioscience startups require significantly more resources to be successful. Third, the updated 2010 NRC doctoral program rankings reveal that the quality of a biological sciences department, when measured by scholarly research output, is positively associated with the creation of startup companies. However, a university must show substantial improvement to meaningfully increase the number of startups. Increasing the biological sciences quality from the 25th percentile to the median increases the incidence of startups by 13%. Universities would likely earn a larger return on their investment by hiring an additional employee in the TTO. We find that TTO size has a significant effect on initial and subsequent university startups. Conditional on creating at least one startup, each additional employee in a TTO increases the number of startups by 7 percent.

II. Background

The Bayh-Dole Act, sponsored by Senators Birch Bayh and Bob Dole, was passed in December, 1980. The legislation allowed US universities, small businesses and non-profits the opportunity to retain ownership of inventions developed using federal research funds. Although universities are permitted an exclusive commercial use for their inventions, the federal funding agencies may also use them royalty-free. Prior to 1980, the US government licensed less than 5% of its patents to industry for commercial development.[3] Because the government provided licenses on a non-exclusive basis, companies were unwilling to invest the substantial amount of money needed to develop the patents into viable products. Since passage of the Act, the number of university patents has grown from almost 500 in 1980 to more than 3,000 in 2005[4]. Faced with recent budget cuts, many universities are exploring ways to create new revenue streams by commercializing some of the discoveries made possible by over 50 billion dollars spent on research in 2008.[5]

[3] www.autm.net/Content/NavigationMenu/TechTransfer/BayhDoleAct/BDTalkPts031407.pdf

[4] Figure 1 shows the growth of university entrepreneurship over time

[5] www.autm.net/AM/Template.cfm?Section=Home&CONTENTID=4513&TEMPLATE=/CM/ContentDisplay.cfm

The path from research idea to commercial product is multifaceted and may take several years. Once a faculty member develops a research idea, the potential invention is disclosed to the TTO. The TTO will then review the invention for patent and future commercial potential. Next, the TTO typically tries to find an industrial partner to license the invention. If one cannot be found, the TTO may work with the researcher to find venture capitalists to fund a startup around the invention. Those TTOs with better connections to venture capital may be more willing to provide assistance in forming a startup. Other TTOs focus more on licensing inventions to established firms.

Previous literature has highlighted the important role of TTOs in successful university entrepreneurship. Chukumba and Jensen (2005) find that the number of licenses and university startups is positively related to the age of a TTO, but not the size of a TTO. Bercovitz et al. (2001) use data from three universities, John Hopkins, Penn State, and Duke to analyze the effect of a TTO's organizational structure on its performance. Faculty themselves are also critical components to a university startup's success. Using MIT data, Scott (2002) finds that faculty with direct and indirect relationships to venture capitalists are more likely to receive funding and create successful startups. Henrekson and Rosenberg (2001), along with Jensen and Thursby (2001), suggest that offering greater incentives for faculty's involvement will drive increased university licensing and startup activity.

Much of the empirical literature uses case studies from specific universities. However, there are some general studies, in addition to Chukumba and Jensen (2005) that look at a larger set of universities. Di Gregorio (2003) uses AUTM data from 1994 to 1998 and finds that increases in faculty quality, measured by the Gourman report, increases the number of startups. O'Shea (2005) uses AUTM data from 1995 to 2001 and NRC rankings to confirm Di Gregorio's results. In addition, he finds that previous startup success, federal and industry funding, and TTO size positively impact the number of startups. A comprehensive summary of the state of the literature is found in Rothaermel, Agung, and Jiang (2007).

III. Data

The primary outcomes of interest for university entrepreneurship in this paper are the number of startups and the number of in-state startups. This data is collected annually by AUTM, the Association of University Technology Managers. AUTM consists of over 350 universities, research institutions, and other agencies associated with commercializing research ideas. Every year, the members complete a comprehensive survey that provides a quantified estimate of productivity and other information which enables researchers to better understand the process of managing and licensing innovative research. We also use this survey to estimate some of the factors (e.g. TTO size) which drive our outcomes of interest.

We link the AUTM survey to a venture capital dataset provided by NVCA, the National Venture Capital Association. Every year, this organization collects information from several sources and publishes a yearbook with comprehensives statistics on the amount and location of venture capital spending. This yearbook contains the amount of venture capital at the state level. In our research, we use the amount of annual venture capital funding for the state in which the university is located.

Next, we use data from the National Research Council (NRC) to understand how faculty size and quality impact university entrepreneurship. In 1995, the NRC published the Assessment of Research Doctorate Programs to measure the quality of doctorate programs in the United States. Faculty respondents to the NRC survey were asked to evaluate the scholarly quality of program faculty on a 5 point scale. A score of '0' denoted "Not sufficient for doctoral education" and a score '5' denoted "Distinguished." For each university's faculty, we compute a size-weighted average of the NRC faculty quality score. We then aggregate the individual faculty quality scores up to the department levels of science and engineering.

With the public release of NRC rankings in 2010, we update our measures of faculty quality. Because of fundamental differences in the methodology of the two surveys, the NRC advises that comparisons between the two studies not be made.[6] The 1995 report evaluated programs on reputation and not on program characteristics. The 2010 survey provides the following four measures[7] which we use to calculate our measure of faculty quality: 1) Average Number of Publications per Allocated Faculty 2) Average Citations per Publication 3) Percent of Allocated Faculty with Grants 4) Awards per Allocated Faculty. NRC determines the number of "Allocated Faculty" using an algorithm based on data about dissertation committee supervision and membership to allocate faculty members on a proportional basis to all departments with which they are affiliated. Because these four measures are correlated in their measure of faculty quality[8], we transform these measures and reduce the dimensionality using principal component analysis. Section IV provides more details of this mathematical transformation.

We also link our data to a data source from the Department of Education. The Integrated Postsecondary Education Data System (IPEDS) is a series of annual surveys given to every university that participates in federal student aid programs. We use this data to determine the number of graduating PhD students in a science or engineering graduate program. We hypothesize that more graduate students may lead to more independent research projects and more assistance to faculty undertaking their own research.

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[6] http://sites.nationalacademies.org/pga/resdoc/pga_051962

[7] See Appendix 1 for measure definitions and construction

[8] See Table 2

Finally, a list of the summary statistics is described in Table 1. The dataset, which consists of approximately 2000 university-year observations representing more than 350 universities, exhibits substantial variation in entrepreneurial activity. Approximately, one-third of the universities are private, and another one-third of universities are land grant universities. More than half of the universities in the dataset have a medical school affiliated with the university. This composition does not change when the sample is restricted to universities which provided data to AUTM on startup activity. The average university initiates two and a half startups a year although that number has been as high as 55 startups in one year. Some universities do not have a TTO while other universities have TTOs that have been in existence for over 80 years and employ more than 95 staff members. The variation in state venture capital funding provides additional evidence for investigating a structural break in the data. In the year 2000, venture capitalists invested more than 42 billion dollars into new companies in the state of California. By 2001, that figure fell to just over 16 billion dollars.

IV. Methodology

Our initial empirical specification takes the following form –

$$Y_{ist} = \beta_0+\beta_1 Univ_{it}+\beta_2 Dept_{it}+\beta_3 Econ_{st}+\beta_4 Year+\varepsilon_{ist}$$

where *i* indexes universities, *s* is a state index, and *t* indexes time (1994 – 2008). Y is our outcome of interest, i.e. university entrepreneurship activity, $Univ_{it}$ is a vector of university characteristics[9], $Dept_{it}$ is a vector of department characteristics[10], $Econ_{st}$ is a vector of

[9] University characteristics include: medical school, private university, land grant university, TTO size, TTO age, federal funding, industrial funding, lagged disclosures, and previous startup.

[10] Department characteristics include: measure of quality, size, and number of graduating PhD students.

economic environment characteristics[11], *Year* controls for a time trend, and ε_{ist} is an error term. We use a negative binomial specification because of the count nature of the data.

Next, we test if a structural break exists in the data after the year 2000. Figure 3 shows a graph of the NASDAQ Composite Index over the years of our dataset, 1994 – 2008. In March, 2000, the NASDAQ reached its peak at over 5000, but fell to under 2500 by the end of the year. We want to test if the steep decline in the NASDAQ reflects a different economic environment for new startups in the 21st century.

The econometric specification for our structural break test takes the following form -

$$Y_{ist} = \beta_0 + \beta_1 Univ_{it} + \beta_2 2001 * Univ_{it} + \beta_3 Dept_{it} + \beta_4 2001 * Dept_{it} + \ldots + \beta_9 2001 + \varepsilon_{ist}$$

where 2001 is a dummy variable equal to 0 if *Year* < 2001 and 1 if *Year* >= 2001. We test the null hypothesis H_0: $\beta_2=0, \beta_4=0, \beta_6=0, \beta_8=0, \beta_9=0.$ If we reject the null hypothesis, then the economic environment in the latter part of the 1990s is significantly different from the one in the early 2000s.

The 2010 NRC Rankings provide several possible measures for faculty quality, including: Average Number of Publications per Allocated Faculty, Average Citations per Publication, Percent of Allocated Faculty with Grants, and Awards per Allocated Faculty. Because these variables are correlated with one another[12], we use principal components analysis (PCA) to reduce these measures into one variable, called the principal component. The principal component is a weighted average of these underlying four indicators. PCA's methodology selects the weights so that the principal component accounts for the maximum variance of the underlying indicators. Table 3 confirms that the data can be reduced to one dimension (i.e. only one component has an eigenvalue greater than one across biological

[11] Economic environment characteristics include: NASDAQ returns, 1 Year T Bill returns, state venture capital, and 10 Year T note returns.

[12] See Table 2

sciences, physical sciences, and engineering departments). Figure 4 also displays the scree plots for each of the three departments.

In addition to applying a negative binomial model to our specification, we also test a hurdle model. A hurdle model may be used whenever a significant threshold must be overcome for the dependent variable to have a positive value. Figure 2, showing the non-trivial amount of zero startups, is evidence that a hurdle model may be a better fit for the data. In the case of university entrepreneurship, significant resources must be expended to generate the first successful startup. Once the first startup is launched, future startups may be significantly less resource intensive. A hurdle model has two different data generating processes. The first process uses a logit model to determine whether the count variable is zero or positive. For all positive values, the conditional distribution is a zero-truncated count model.

V. Results

V.I. Additional Years of Data

Columns 1 and 2 in Table 4 display updated results using the identical empirical specification in Jensen (2011) with additional years of AUTM data. The additional years of data confirm many of the results previously found. Private universities and land grant universities are negatively associated with entrepreneurship activity, while the quality of engineering faculty, TTO Age, and previous disclosures are positively associated. In addition, sources of federal and industrial funding are strongly predictive of the number of startup companies.

Column 3 in Table 4 adds additional controls including the number of PhD students, quadratic terms for TTO age and size, economic environment variables, and whether or not a startup was previously started at the university. The addition of these controls confirms the results previously found in the literature[13] and also produces new findings. Because the coefficents in a negative binomial regression can be difficult to interpret, column 1 in Table 5 presents the coefficients as incidence rate ratios. For example, with a coefficient of 1.5650 on the *Previous Startup* variable, one would interpret this result as "universities that created a startup in the past are expected to have a startup rate 1.5650 times greater than those universities that did not create a startup previously."

We also find that university entrepreneurship is more common in bad economic times. As NASDAQ returns decrease, the number of university startups increases. In 2009, if the NASDAQ declined by 10 percentage points, an additional 20 university startups would have been created. Increasing the number of graduating engineering or physical science PhD students does not increase the number of startups. An increase in biological science PhD students is even associated with a decrease in the number of startups. Finally, we find that increasing the size of a TTO is associated with a higher number of startups although the marginal effect is diminishing[14].

Column 2 in Table 5 presents results using the updated 2010 NRC graduate program rankings. The size of the physical sciences department and engineering department is positively related to the number of startups. However, while engineering faculty quality was positively associated with startups in the 1995 NRC rankings that is no longer the case using the 2010 NRC rankings. Unfortunately, the measure of quality is not directly comparable between the two rankings. In the 1995 NRC rankings, department quality is measured by

[13] Notably, all five predictors of university entrepreneurship in O'Shea (2005) are confirmed – 1) Previous success in technology transfer 2) High NRC quality rating 3) High levels of federal funding 4) High levels of industrial funding 5) Size of TTO.

[14] This finding is due to the additional controls and years of data. When our dataset is limited to the years 1994-2004 in columns 1 and 2 of Table 4, we do not find a statistically significant effect of TTO size. In Belenzon and Schankerman (2009), the authors also find that the effect of TTO size on licensing activity to be statistically insignificant. When we restrict our dataset to the same years of data, 1995 – 2001, we confirm their finding of TTO size. It appears that the additional years of data beyond 2001 are driving the significant effect for TTO size.

surveying faculty of other universities. In 2010, department quality is measured as a composite measure of research output (e.g. number of publications, grants, etc.). Although we cannot compare quality measures over time, we can report that an engineering department's quality, as measured by scholarly research output, does not appear to be correlated with creating startup companies. In contrast, the quality of a biological sciences department, when measured by scholarly research output, is positively associated with creating startup companies.

V.II. Structural Break

Table 6 shows the coefficients on the interaction terms which are statistically significant in the following econometric specification for a structural break -

$$Y_{ist} = \beta_0 + \beta_1 Univ_{it} + \beta_2 2001 * Univ_{it} + \beta_3 Dept_{it} + \beta_4 2001 * Dept_{it} + \ldots + \beta_9 2001 + \varepsilon_{ist}$$

The test of the null hypothesis H_0: $\beta_2=0, \beta_4=0, \beta_6=0, \beta_8=0, \beta_9=0$ produces a chi-square statistic with a p-value of 0.0012. Therefore, we reject the null hypothesis and conclude that there is a structural difference in how startups are generated after the year 2000. In particular, Table 6 indicates that engineering quality and the size of the biological sciences department are more important after 2000. These two findings suggest that venture capitalists are now more selective about where they invest their capital and that bioscience startups require significantly more resources to be successful. The number of disclosures and whether or not a university has successfully created a new startup are both less important after 2000.

V.III. Hurdle Model

Columns 1 and 2 in Table 7 provide the result of a hurdle model specification using only data since 2001. The first column is the result from the logit model which determines whether the number of startups is zero or positive. The second column provides the results from a zero-truncated count model. That is, what factors determine entrepreneurial success once a startup has already been created? The hurdle model specification produces new insights into the nature of university entrepreneurship. The size of an engineering or physical sciences department does not determine whether a startup is created, but once a startup has been successfully created, a larger department is associated with a higher number of startups. In contrast, the number of physical science and engineering PhD students is significantly related to the creation of a startup, but for universities with successful entrepreneurship programs, the number of PhD students and startup companies may even be negatively related. Throughout the different empirical specifications, one important variable has consistently remained significant – lagged disclosures. In order to produce a startup, there must be a large number of disclosures in the pipeline. These are the lifeblood of startups.

Columns 3 and 4 in Table 7 provide results for the number of in-state startups using the hurdle model specification with data beginning in 2001. Consistent with the overall startup findings, land grant universities are negatively related to in-state startups. Almost all of the other covariates for in-state startups are also consistent in sign and magnitude with overall startup findings. Private universities are much less likely to be associated with generating a startup company in-state compared to public universities that are not land-grant, suggesting that in-state startups may be partly influenced by political pressure. Indeed, Belenzon and Schankerman (2009) find that public universities can be quite susceptible to local development pressure.

V.IV. Alternative Specifications

Despite the inclusion of a robust set of controls, there still may be a concern that our empirical specification fails to account for a university's underlying capacity and propensity for entrepreneurship. Because a fixed effects model would be unable to estimate the effects of a permanent characteristic over our sample time period (e.g. presence of a medical school), we follow an alternative approach that uses the pre-sample history of entrepreneurial activity to control for a university's entrepreneurial environment. To account for this unobservable heterogeneity, we measure a university's knowledge stock over a pre-sample time period, namely 1965-1990. We follow Belenzon and Schankerman (2009) and use the total number of patents issued by the United States Patent and Trademark Office between 1965 and 1990 as a proxy for a university's fixed characteristic for entrepreneurial activity. Blundell (1995) shows that using a pre-sample measure of innovation information can approximate the university specific entrepreneurial effect. Using Google Patent Search, we include all of the patents that were issued by the USPTO to each university in the dataset as a control. The results in column 1 of Table 8 show similar point estimates on our primary variables of interest.

Next, we investigate a random effects negative binomial (REBN) model to exploit the fact that our dataset is an unbalanced panel. An REBN model requires the assumption that the regressors and the university entrepreneurial characteristic are uncorrelated. The results of the model are shown in column 2 of Table 8. Once again, the quality of the biological sciences faculty and the size of the TTO are statistically and economically significant. For example, each additional employee in the TTO increases the rate of annual startups by 10 percent.

V.V. Granger Causality

Given that we find TTO size can play a significant role in university startups, we want to test which one comes first chronologically. Do startups lag TTOs or do successful university startups result in a larger TTO? A test for granger causality can be used to distinguish between the two. If TTO size "granger-causes" startups, then past values of TTO size contain information that helps predict startups beyond past values of startups alone.

The following equation illustrates the test for granger causality –

$$Startups_{ist} = \beta_0+\beta_1 Startups_{it-1}+\beta_2 Startups_{it-2}+\beta_3 TTOSize_{it-1}+\beta_4 TTOSize_{it-2}+\beta_5 X_{ist}+\varepsilon_{it}$$

Table 9 shows that TTO size leads university startups.

VI. Conclusions

This paper confirms several previous results in the literature while also contributing new findings. We find that university entrepreneurship is more common in bad economic times. Also, the importance of factors which were responsible for university entrepreneurial activity prior to the dot-com collapse changes after the year 2000. Universities need to take a new look at how startups are created in this new economic environment. Although the quality of the biological sciences faculty matters for startup activity, substantial improvement is difficult. Increasing the size of the TTO may provide a better return on investment. The hurdle model shows that recommendations for how universities can drive future entrepreneurship depend on whether a university has successfully created a startup firm in the past. Despite these new findings, more work remains to be done. In particular, there are likely better proxies for faculty quality than the ones we currently employ.

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Figure 1

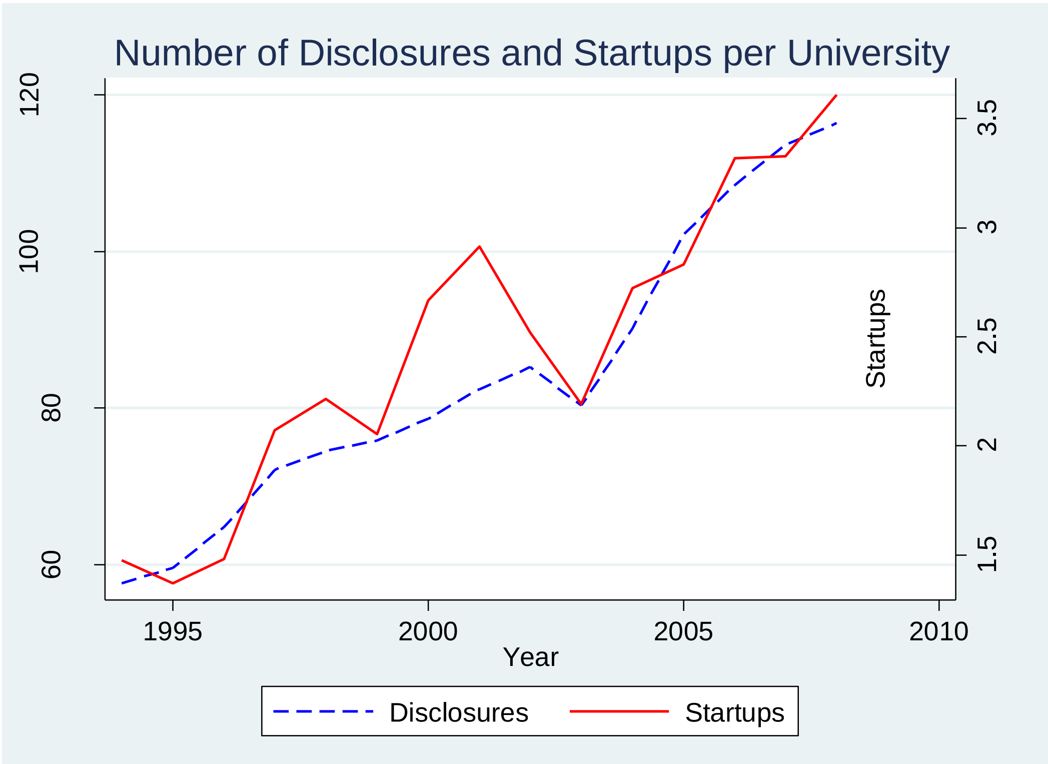

Number of Disclosures and Startups per University
120
100
80
60
3.5
3
2.5
2
1.5
Startups
1995
2000
2005
2010
Year
Disclosures
Startups

Figure 2

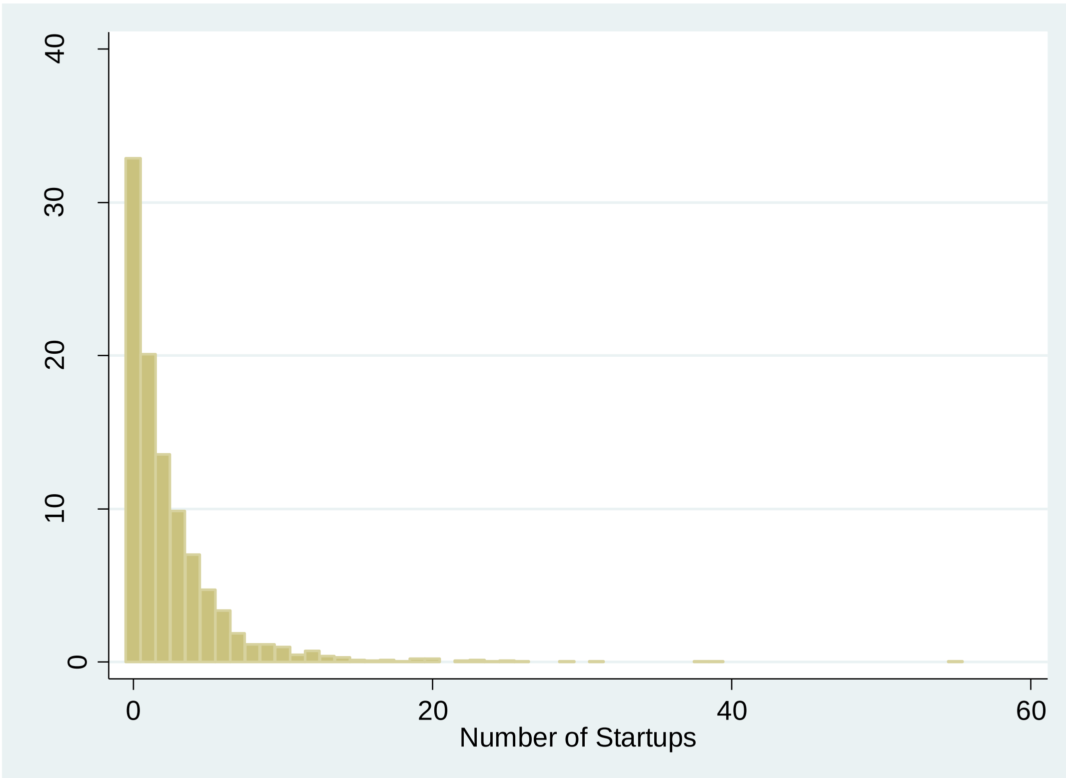


Figure 3: NASDAQ Composite Index

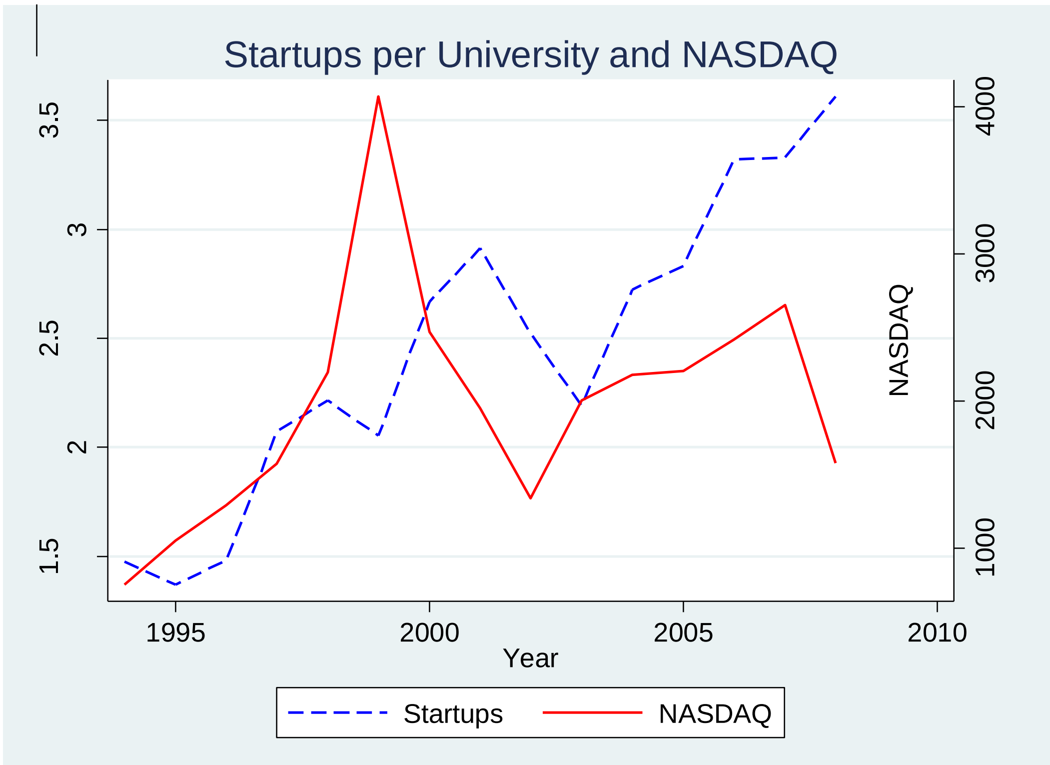
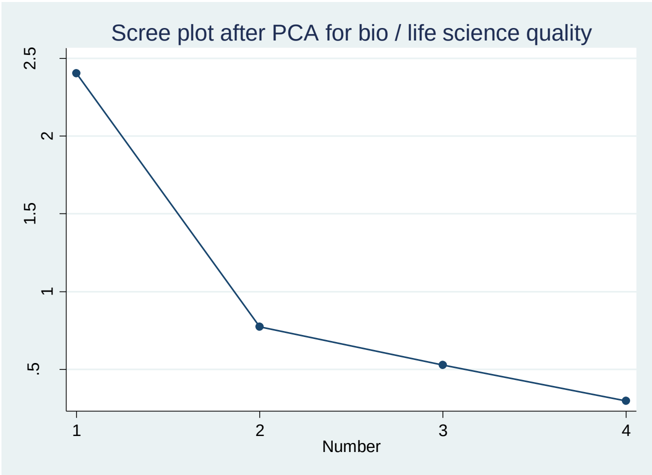
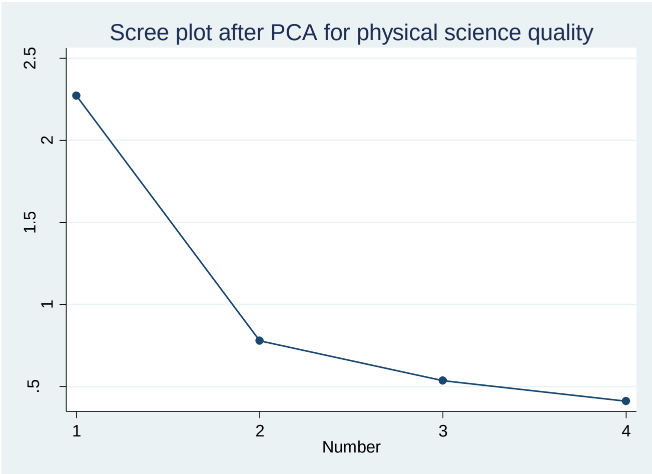


Figure 4: Scree plots after Principal Components Analysis (PCA)





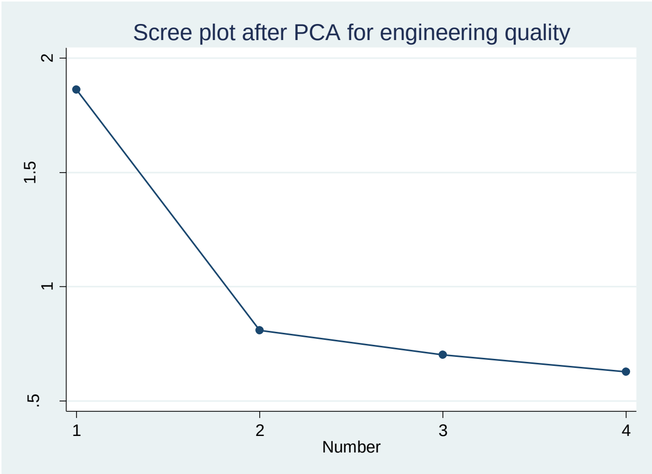


Table 1: Summary Statistics

Variable	**Mean**	**Std. Dev**	**Min**	**Max**	**Observations (University-Year)**
Startups	2.48	3.77	0	55	2067
Startups in state	2.15	3.29	0	49	1650
Land grant university	.31	.46	0	1	2582
Private university	.31	.46	0	1	2598
Medical school	.56	.50	0	1	2835
Sci Size (1995 NRC)	244.12	328.72	9	3225	2332
Eng Size (1995 NRC)	100.32	86.41	7	423	1692
Bio Size (2010 NRC)	127.02	124.04	0	656.48	2295
Phy Size (2010 NRC)	107.33	85.22	0	414.52	2295
Eng Size (2010 NRC)	82.30	94.69	0	547.78	2295
Bio PhD Grads	17.83	38.85	0	738	4143
Phy PhD Grads	16.23	31.94	0	459	4128
Eng PhD Grads	22.32	48.02	0	715	4017
TTO Size	4.05	6.20	0	95	2271
TTO Age	14.42	12.41	0	83	2372
Patents1965-1990	38.59	79.78	0	570	3264
Fed Funding ($MM)	133.0	193.0	0	2440.0	2344
Ind Funding ($MM)	15.9	26.5	0	363.0	2308
Vent Cap ($MM)*	1060.0	3070.0	0	42600.0	4593
Nasdaq	10.60	34.69	-68.18	84.30	2737
1 Year T Bill Return	4.28	1.45	1.24	6.11	2585
10 Year T Note Return	5.53	1.11	4.01	7.86	2585

* Venture capital is aggregated to the state.
Federal and industrial funding is by university.

Table 2: Correlations of Faculty Quality Measures

Biological Sciences

	Pub / Faculty	Citations / Pub	Grants	Awards
Pub / Faculty	1.0000			
Citations / Pub	0.4833	1.0000		
Grants	0.5667	0.4370	1.0000	
Awards	0.5602	0.5009	0.2327	1.0000

Physical Sciences

	Pub / Faculty	Citations / Pub	Grants	Awards
Pub / Faculty	1.0000			
Citations / Pub	0.5874	1.0000		
Grants	0.4854	0.4986	1.0000	
Awards	0.3270	0.3172	0.2748	1.0000

Engineering

	Pub / Faculty	Citations / Pub	Grants	Awards
Pub / Faculty	1.0000			
Citations / Pub	0.3410	1.0000		
Grants	0.2609	0.2858	1.0000	
Awards	0.3495	0.2670	0.2111	1.0000

Table 3: Principal Components

Biological Sciences

Component	Eigenvalue	Difference	Proportion	Cum. Variation
Comp1	2.40314	1.62933	0.6008	0.6008
Comp2	.773807	.247335	0.1935	0.7942
Comp3	.526473	.229893	0.1316	0.9259
Comp4	.29658	.	0.0741	1.0000

Physical Sciences

Component	Eigenvalue	Difference	Proportion	Cum. Variation
Comp1	2.2712	1.49134	0.5678	0.5678
Comp2	.779858	.242873	0.1950	0.7628
Comp3	.536985	.125023	0.1342	0.8970
Comp4	.411962	.	0.1030	1.0000

Engineering

Component	Eigenvalue	Difference	Proportion	Cum. Variation
Comp1	1.86222	1.05297	0.4656	0.4656
Comp2	.809256	.107706	0.2023	0.6679
Comp3	.70155	.0745779	0.1754	0.8433
Comp4	.626972	.	.1567	1.0000

Table 4: Number of Startups, Negative Binomial Regression

	(1) Through 2004	(2) Through 2008	(3) Additional Controls
Medical School	-0.0251	-0.0204	-0.0134
	(0.0769)	(0.0643)	(0.0717)
Land Grant	-0.1834***	-0.2029***	-0.1369**
	(0.0677)	(0.0568)	(0.0636)
Private	-0.2265***	-0.1970***	-0.1962***
	(0.0828)	(0.0667)	(0.0756)
Science Size	-0.0004***	-0.0004***	-0.0001
	(0.0001)	(0.0001)	(0.0002)
Science Quality	-0.0117	0.0621	0.0678
	(0.0916)	(0.0739)	(0.0936)
Engineering Size	0.0005	0.0010**	0.0004
	(0.0005)	(0.0005)	(0.0007)
Engineering Quality	0.4010***	0.2644***	0.2548***
	(0.0917)	(0.0736)	(0.0870)
TTO Size	0.0033	-0.0013	0.0307***
	(0.0075)	(0.0060)	(0.0111)
TTO Age	0.0045*	0.0047**	0.0213***
	(0.0025)	(0.0020)	(0.0077)
Lag Disclosures	0.0026***	0.0025***	0.0022***
	(0.0005)	(0.0004)	(0.0004)
Ln Federal Funds	0.1588**	0.1515***	0.1075*
	(0.0656)	(0.0524)	(0.0628)
Ln Industrial Funds	0.1604***	0.0968***	0.0678**
	(0.0455)	(0.0310)	(0.0332)
Ln VC Funding	0.0290**	0.0183*	0.0006
	(0.0126)	(0.0099)	(0.0116)
Nasdaq	-0.0012	-0.0008	-0.0027**
	(0.0007)	(0.0007)	(0.0011)
Year	0.0349***	0.0301***	0.0238
	(0.0103)	(0.0072)	(0.0201)
TTO Size Sq			-0.0004***
			(0.0001)
TTO Age Sq			-0.0003***
			(0.0001)
PhDs Biological Sci			-0.0035**
			(0.0015)
PhDs Physical Sci			0.0019
			(0.0019)
PhDs Engineering			0.0011
			(0.0010)
1 Yr T Bill Return			0.0158
			(0.0406)
10 Yr T Note Return			0.0129
			(0.1276)
Previous Startup			0.4479***
			(0.1211)
Pseudo R^2	0.1714	0.1595	0.1732
Observations	851	1160	912

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Number of Startups, Negative Binomial Regression, Incidence Rate Ratio

	(1) NRC 1995, IRR	(2) NRC 2010, IRR
Medical School	.9867	.9189
	(-0.19)	(-0.99)
Land Grant	.8721**	.6774***
	(-2.15)	(-4.47)
Private	.8219***	.8623*
	(-2.59)	(-1.74)
Science Size	.9999	
	(-0.49)	
Science Quality	1.0701	
	(0.72)	
Bio Size		.9999
		(-0.36)
Phy Size		1.0031***
		(4.47)
Bio Quality		1.0939***
		(2.98)
Phy Quality		1.0029
		(0.11)
Engineering Size	1.0004	1.0010*
	(0.67)	(1.62)
Engineering Quality	1.2901***	.9798
	(2.93)	(-0.66)
TTO Size	1.0312***	1.1616***
	(2.76)	(4.89)
TTO Size Sq	.9996***	.9924***
	(-3.34)	(-4.45)
TTO Age	1.0215***	1.0420***
	(2.76)	(4.71)
TTO Age Sq	.9997***	.9994***
	(-2.74)	(-4.64)
Lag Disclosures	1.0023***	1.0025***
	(5.36)	(5.64)
Ln Federal Funds	1.1134*	.9370
	(1.71)	(-0.97)
Ln Industrial Funds	1.0702**	1.0070
	(2.04)	(0.22)
Ln VC Funding	1.0006	1.0108
	(0.05)	(0.89)
Nasdaq	.9974**	.9978*
	(-2.43)	(-1.92)
PhDs Biological Sci	.9965***	1.0004
	(-2.43)	(0.19)
PhDs Physical Sci	1.0019**	.9991
	(0.96)	(-0.36)
PhDs Engineering	1.0011	1.0003
	(1.13)	(0.25)
1 Yr T Bill Return	1.0159	1.0174
	(0.39)	(0.36)
10 Yr T Note Return	1.0130	1.0088
	(0.10)	(0.40)
Year	1.0241	1.0079
	(1.18)	(0.06)
Previous Startup	1.5650***	1.4457***
	(3.70)	(2.80)
Observations	912	744

Z scores in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Structural Break Test

	(1) Structural Break (2001)
Post2000	-86.7660
	(288.7675)
Post2000 * PreviousStartup	-0.9462**
	(0.4136)
Post2000 * Bio Size	0.0014*
	(0.0008)
Post2000 * Eng Quality	0.1124*
	(0.0653)
Post2000 * Phy Quality	-0.1049**
	(0.0525)
Post2000 * Lag Disclosures	-0.0032***
	(0.0011)
Post2000 * Phd Biological Sci	-0.0082*
	(0.0043)
Post2000 * 1 Yr T Bill Return	0.4702*
	(0.2667)
Pseudo R^2	0.1926
Observations	744

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
X(26) = 53.36; p-value = 0.0012

Table 7: Hurdle Model

	(1) Hurdle Model (>= 2001) Logit, OR	(2) Poisson, IRR	(3) Startups in-state (>= 2001) Logit, OR	(4) Poisson, IRR
Medical School	0.9299	0.9049	0.5598	0.9358
	(-0.16)	(-1.13)	(-1.36)	(-0.66)
Land Grant	0.9498	0.7578***	0.3617**	0.8147**
	(-0.11)	(-3.13)	(-2.29)	(-2.08)
Private	1.3751	0.8847	0.3769**	0.8395*
	(0.67)	(-1.38)	(-2.20)	(-1.73)
Bio Size	1.0051	1.0000	1.0010	0.9999
	(1.49)	(0.04)	(0.33)	(-0.13)
Eng Size	0.9938	1.0013**	0.9953	1.0011
	(-0.95)	(2.04)	(-0.84)	(1.52)
Phy Size	0.9933	1.0027***	0.9998	1.0023***
	(-1.43)	(3.71)	(-0.04)	(2.86)
Bio Quality	1.2714	1.1245***	1.3791*	1.1516***
	(1.22)	(3.65)	(1.69)	(3.92)
Eng Quality	0.9150	1.0094	1.2710	1.0109
	(-0.5)	(0.29)	(1.41)	(0.29)
Phy Quality	0.9025	0.9807	0.7280*	1.0386
	(-0.49)	(-0.75)	(-1.76)	(1.27)
TTO Size	1.4114	1.0727**	1.2348	1.0738*
	(1.41)	(1.99)	(0.86)	(1.78)
TTO Size Sq	0.9664*	0.9974	0.9890	0.9968
	(-1.88)	(-1.39)	(-0.50)	(-1.49)
TTO Age	0.9877	1.0327***	1.0379	1.0383***
	(-0.26)	(3.16)	(0.87)	(3.28)
TTO Age Sq	1.0001	0.9995***	0.9995	0.9995***
	(0.15)	(-3.44)	(-0.82)	(-3.41)
Lag Disclosures	1.0227**	1.0015***	1.0125**	1.0016***
	(2.95)	(3.81)	(2.07)	(3.57)
Ln Federal Funds	0.5388	0.9936	0.8787	0.9770
	(-1.54)	(-0.09)	(-0.38)	(-0.30)
Ln Industrial Funds	0.9432	0.9921	1.1784	0.9757
	(-0.28)	(-0.29)	(1.13)	(-0.86)
Ln VC Funding	1.0073	0.9928	1.0073	1.0004
	(0.17)	(0.55)	(0.18)	(0.02)
Nasdaq	0.9977	0.9999	0.9937	1.0000
	(-0.25)	(-0.04)	(-0.75)	(0.01)
PhDs Biological Sci	0.9761	0.9980	0.9901	0.9973
	(-1.22)	(-0.93)	(-0.61)	(-1.08)
PhDs Physical Sci	1.0545**	0.9975	1.0406*	0.9935**
	(2.1)	(-0.87)	(1.83)	(-2.02)
PhDs Engineering	1.0477**	0.9994	1.0117	1.0007
	(2.43)	(-0.44)	(0.84)	(0.45)
Year	1.0257	0.9957	0.9207	0.9890
	(0.13)	(-0.13)	(-0.48)	(-0.30)
1 Yr T Bill Return	1.2443	1.0137	1.4780	0.9999
	(0.6)	(0.2)	(1.13)	(-0.00)
10 Yr T Note Return	0.8166	1.2091	0.4637	1.1661
	(-0.15)	(0.78)	(-0.59)	(0.56)
Observations	429	342	429	318

Z scores in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Additional Specifications

	(1) Hurdle Model with Patent Stock Control Logit, OR	(2) Poisson, IRR	(3) Random Effects Negative Binomial IRR
Medical School	0.9416	0.9027	0.8856
	(-0.13)	(-1.16)	(-0.91)
Land Grant	0.9244	0.7407^{***}	0.6454^{***}
	(-0.16)	(-3.43)	(-3.28)
Private	1.3354	0.8808	0.8902
	(0.60)	(-1.44)	(-0.88)
Bio Size	1.0047	1.0000	1.0004
	(1.33)	(0.00)	(0.69)
Eng Size	0.9938	1.0017^{***}	1.0023^{***}
	(-0.94)	(2.60)	(2.47)
Phy Size	0.9929	1.0025^{***}	1.0031^{***}
	(-1.49)	(3.43)	(2.96)
Bio Quality	1.2762	1.0729^{**}	1.1052^{*}
	(1.24)	(1.96)	(1.88)
Eng Quality	0.9029	1.0110	1.0242
	(-0.56)	(0.33)	(0.49)
Phy Quality	0.9120	0.9816	0.9659
	(-0.44)	(-0.70)	(-0.83)
TTO Size	1.3927	1.0552	1.1083^{**}
	(1.36)	(1.49)	(2.14)
TTO Size Sq	0.9667^{*}	0.9979	0.9957
	(-1.89)	(-1.09)	(-1.60)
TTO Age	0.9919	1.0332^{***}	1.0292^{*}
	(-0.17)	(3.13)	(1.95)
TTO Age Sq	1.0000	0.9994^{***}	0.9995^{***}
	(-0.01)	(-3.97)	(-2.53)
Lag Disclosures	1.0228^{***}	1.0014^{***}	1.0014^{**}
	(2.95)	(3.19)	(2.41)
Ln Federal Funds	0.5515	1.0374	0.9315
	(-1.48)	(0.51)	(-0.68)
Ln Industrial Funds	0.9274	0.9943	1.0026
	(-0.36)	(-0.21)	(0.08)
Ln VC Funding	1.0123	0.9915	1.0001
	(0.28)	(-0.64)	(0.01)
Nasdaq	0.9975	0.9999	0.9994
	(-0.27)	(-0.03)	(-0.30)
PhDs Biological Sci	0.9769	0.9997	1.0010
	(-1.17)	(-0.12)	(0.37)
PhDs Physical Sci	1.0540^{**}	0.9942^{*}	0.9959
	(2.09)	(-1.90)	(-1.02)
PhDs Engineering	1.0469^{**}	0.9985	0.9988^{**}
	(2.38)	(-1.13)	(-0.71)
Year	1.0250	1.0080	
	(0.13)	(0.24)	
1 Yr T Bill Return	1.2484	1.0141	1.0591
	(0.60)	(0.21)	(1.39)
10 Yr T Note Return	0.8097	1.2540	1.1050
	(-0.15)	(0.93)	(0.52)
Patents1965-1990	1.0035	1.0019^{***}	1.0014
	(0.44)	(3.01)	(1.55)
Observations	429	342	428

Z scores in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Granger Causality

	(1) Startups	(2) TTO Size
L.Startups	0.0476***	-0.0015
	(0.0087)	(0.0057)
L2.Startups	0.0082	-0.0009
	(0.0089)	(0.0053)
L.TTO Size	-0.0253**	0.0213***
	(0.0104)	(0.0059)
L2.TTO Size	0.0360***	0.0354***
	(0.0108)	(0.0057)
Medical School	-0.0223	0.2137***
	(0.0722)	(0.0518)
Land Grant	-0.1612**	-0.0079
	(0.0637)	(0.0465)
Private	-0.2647***	-0.1090**
	(0.0774)	(0.0542)
Science Size	-0.0003	0.0004***
	(0.0002)	(0.0001)
Science Quality	0.1098	0.0410
	(0.0998)	(0.0713)
Engineering Size	0.0007	0.0004
	(0.0007)	(0.0005)
Engineering Quality	0.2522***	0.1937***
	(0.0891)	(0.0614)
TTO Age	0.0183**	0.0151***
	(0.0082)	(0.0057)
TTO Age Sq	-0.0003**	-0.0001
	(0.0001)	(0.0001)
Lag Disclosures	0.0010**	0.0004*
	(0.0004)	(0.0002)
Ln Federal Funds	0.1315**	0.1866***
	(0.0643)	(0.0475)
Ln Industrial Funds	0.0380	0.0115
	(0.0327)	(0.0227)
Ln VC Funding	0.0064	0.0103
	(0.0134)	(0.0095)
Nasdaq	-0.0019*	-0.0014*
	(0.0011)	(0.0008)
PhDs Bio/Life Sci	-0.0011	-0.0024**
	(0.0016)	(0.0010)
PhDs Physical Sci	0.0008	-0.0041***
	(0.0020)	(0.0013)
PhDs Engineering	-0.0001	-0.0006
	(0.0010)	(0.0007)
1 Yr T Bill Return	0.0171	-0.0075
	(0.0420)	(0.0300)
10 Yr T Note Return	0.0356	-0.0589
	(0.1340)	(0.0961)
Year	0.0255	0.0085
	(0.0201)	(0.0144)
Previous Startup	0.7693***	0.4901**
	(0.2769)	(0.1937)
Pseudo R^2	0.1861	0.2999
Observations	739	743

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
(1) Test L.Size = L2.Size = 0; Prob > chi2 = 0.0034
(2) Test L.Startup = L2.Startup = 0; Prob > chi2 = 0.9212

Appendix 1: 2010 NRC Measures of Faculty Quality

Source: A Guide to the Methodology of the National Research Council Assessment of Doctorate Programs (2009)

Publications per Allocated Faculty: Data from the Institute for Scientific Information were used to construct this variable. It is the average over the seven years, 2000-2006, of the number of articles for each allocated faculty member divided by the total number of faculty allocated to the program. Data were obtained by matching faculty lists supplied by the programs to the ISI list of publications.

Average Citations per Publication: Data from the Institute for Scientific Information were used to construct this variable. It is the per-year average of the number of allocated citations in the years 2000-2006 to papers published during the period 1981-2006 by program faculty divided by the allocated publications that could contribute to the citations. For example, the number of allocated citations for a faculty member in 2003 is found by taking the 2003 citations to that faculty member's publications between 1981 and 2003. These counts are summed over the entire faculty in the program and divided by the sum of the allocated publications to the program in 2003.

Percent of Faculty with Grants: Data from the faculty questionnaire were used to construct this variable. The faculty questionnaire asks whether a faculty member's work is currently supported by an extramural grant of contract (E1). The total of faculty who answered this question in the affirmative was divided by the total respondents in the program and the percentage was calculated.

Awards per Allocated Faculty: Data from a review of 1,393 awards and honors from various scholarly organizations were used for this variable. The awards were identified by the committee as "Highly Prestigious" or "Prestigious" with the former given a weight of 5. The award recipients were matched to the faculty in all programs, and the total awards for a faculty member in a program was the sum of the weighted awards times the faculty member's allocation to that program. These awards were added across the faculty in a program and divided by the total allocation of the faculty in the program.