SOCIAL NETWORKS AND FIRM FORMATION:

A STUDY OF BOSTON'S BIOTECHNOLOGY SECTOR

By

Vishwanath Kanda

Post Graduate Diploma in Management
Indian Institute of Management, Ahmedabad (1999)

Bachelor of Technology (Chemical Engineering)
Indian Institute of Technology, Madras (1997)

Submitted to the Engineering Systems Division
in Partial Fulfillment of the Requirements for the Degree of

Master of Science in Technology and Policy

at the

Massachusetts Institute of Technology

June 2004

Signature of Author..
Technology and Policy Program, Engineering Systems Division
May 7, 2004

Certified by..
Fiona Murray
Michael M. Koerner '49 Career Development Professorship
Management of Technological Innovation & Entrepreneurship (MTIE)
Sloan School of Management
Thesis Supervisor

Accepted by..
Dava Newman
Associate Professor of Aeronautics and Astronautics and Engineering Systems
Director, Technology and Policy Program

SOCIAL NETWORKS AND FIRM FORMATION:

A STUDY OF BOSTON'S BIOTECHNOLOGY SECTOR

By,

Vishwanath Kanda

Submitted to the Engineering Systems Division on May 7, 2004
in partial fulfillment of the requirements for the Degree of
Master of Science in Technology and Policy

ABSTRACT
This research focuses on two specific research problems in the context of innovation in the biotech industry. These research problems map to the two phases of innovation process – creation of new scientific expertise (Phase I) and commercialization of that new expertise (Phase II).

The research problem in Phase I, examines determinants of productivity in the creation of new scientific expertise, specifically following scholarship in the sociology of networks, assessing the impact of patterns of scientific research networks on research productivity. The setting for the study is a group of research scientists associated with the Du Pont - MIT Alliance. Findings suggest that optimal research networks should have a large number of relatively strong links and avoid over-dependence on a few research collaborators, to enhance research productivity.

With respect to Phase II and the transformation of scientific ideas into commercial products, existing innovation literature has identified several ingredients for commercial success, and in particular, for start-up ventures: reputed management teams, BODs (Board of Directors), SABs (Scientific Advisory Boards) and prominent VC (venture capital) firms. However the relative influence of the inventor's reputation versus the quality of the research idea in assembling these necessary constituents has not been researched. The study sample for the research problem under Phase II, consisted of all the biotech start-ups in the Massachusetts area, founded after 1995. The research findings highlight the usage of 'signaling' (reputation in this case) in assembling reputed teams. The study also shows diminishing returns to such signaling as the uncertainty reduces.

The implications of these finding can be broadly drawn at the level of technology policy and at the unit level of a firm. Technology policy can influence the organization of university research networks as well as make funding allocation decisions. Individual firms can use these results to shape their collaboration with academia. The results also send a strong signal that if a research idea attains prominence, it can be successfully commercialized regardless of the inventor reputation.

Thesis Supervisor: Fiona Murray,
Michael M. Koerner '49 Career Development Professorship
Management of Technological Innovation & Entrepreneurship (MTIE)
Sloan School of Management

ACKNOWLEDGEMENT

I would like to thank my advisor, Prof. Fiona Murray, who has been the driving force behind this thesis. I have gained tremendously under her tutelage as she constantly posed me challenging research problems, holding me to her high standards as I grappled with them. I would also like thank Prof. Ezra Zuckerman, who despite a short interaction has been an encouraging influence. I owe my gratitude to the DuPont MIT Alliance (DMA) for my Fellowship, which allowed me the time to seek out a research group I was interested in working with. Thanks are also due to Sydney Miller, Program Administrator at TPP, who has been very patient and helpful each time I reached out to her.

I would like to thank my parents and brother for their constant encouragement over the years. I finally would like to thank my wife Shaheen, who has been my support and inspiration.

TABLE OF CONTENTS

TABLE OF FIGURES

CHAPTER 1: INTRODUCTION

Biotechnology: The Importance of Start-Up Firms and Research in Academia

The biotechnology industry has witnessed tremendous growth in the last three decades, due to the success of some pioneering drugs like human insulin (Genentech), erythropoietin (Amgen) and TPA (Genentech). These innovations and drugs like them offer the best hope against complex illnesses like cancer and AIDS among others. The pharmaceutical industry's importance in the US economy is growing (as mirrored in the recent reconstitution of the Dow Jones Index) and biotech companies play key role in directing that change. The biotech sector generates $30 billion in annual sales, employs about 200,000 people and has $90 billion invested in publicly traded companies (Ernst & Young).

The key driver of growth in this industry is innovation. Start-up companies and research at universities have played a crucial role in driving the innovation engine of this industry. This has been in evidence from the very beginning of the industry, when the development of recombinant technology by Herbert Boyer (UCSF) and Stanley Cohen (Stanford) and the formation of a company called Genentech to commercialize it, is said to have ushered in the biotechnology industry. The growing venture capital industry made it easier for scientists with cutting edge ideas to start companies to commercialize their science.

This trend of companies germinating from university labs intensified with the huge IPO success of Genentech in 1980. Universities also did not lose time in realizing the potential of the research they were conducting. Research shows that the patenting and licensing activities in leading universities significantly increased due to biomedical research (Mowery et al, 1993). This trend was supported by the Bayh Dole Act of 1980, which allowed universities to seek patents from research that came from public funding. Research from leading universities plays an important role in the creation of new ventures through spinoffs and technology licensing. In the Massachusetts region alone, MIT and Harvard University are directly or indirectly related to more than 40% (based on our analysis) of all the biotech start-ups in that area. Despite the growing interest of large pharmaceutical companies in biotech, start-up companies continue to be at the cutting edge of research in this industry.

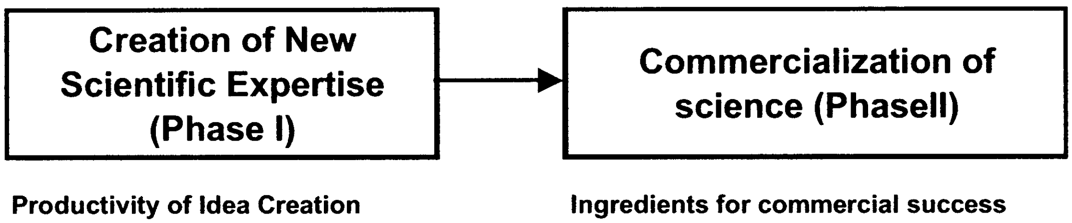
Innovation Research in Biotechnology

The biotech industry is witness to the launch of several new technologies and business alliances every year. Given that the industry is still in the growth phase of its cycle, scores of start-up companies are crated every year while several more become extinct (through either Chapter 11 (reorganization) or Chapter 7 (liquidation) and acquisition). This churn in the industry along with the scorching pace of technological and business model innovation in the biotech industry has attracted the attention of innovation researchers. Researchers are interested in understanding the two phases of innovation (Utterback model of innovation, 1971): Creation of New Scientific Expertise and Commercialization of Science. More specifically, they are interested in exploring the factors that assist in both the above.

Overall Research Problem

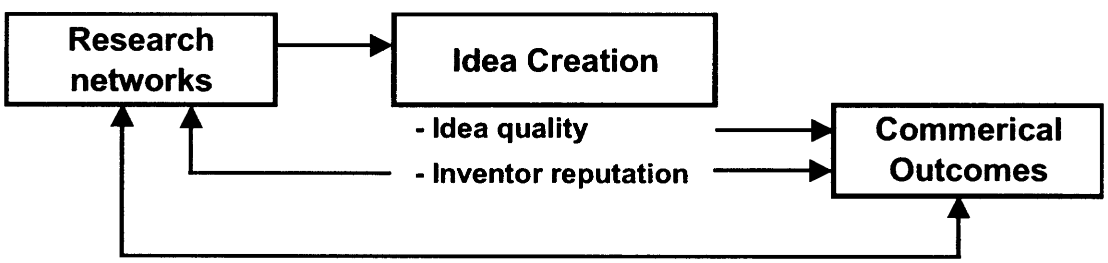
The research problem addressed in this thesis is set up using a slightly modified version of the Utterback model of innovation (mentioned above). Phase I (Creation of New Scientific Expertise) is essentially about investing and developing new scientific capabilities in response to a pre-defined need. It consists of the following sub-processes: recognition of external market need, recognition of a technical means to meet this need and the synthesis of this information to develop a new technology/science. Phase II (Commercialization of this science) consists of taking the product concept from Phase I through to the market place. It involves the following steps: devising a business model that best suits the new technology, obtaining financing, setting up a management team and oversight boards, building commercial expertise (sales and marketing and supply chain) and launching the product. However, it should be noted that this is not necessarily a linear process. Often times, the new technology has to be modified based on feedback loops from Phase II. Within this overall process model of innovation, I have focused on specific elements within the two Phases (see figure 1).

Figure 1: Process model of innovation



The broad problem this thesis focuses on under Phase I is that of understanding the impact of scientific research networks on productivity. Under Phase II, this thesis focuses on the relative impact of the starting conditions (quality of the scientific idea(s), reputation of the inventor(s)) on the ability of the start-up to successfully commercialize its science. The overall research problem can be recast as below (see Figure 2)

Figure 2: Overall research schematic



Research Networks

The wide prevalence of collaborative research in science and its understood benefits (increasing bandwidth for scientists and cross-pollination) makes research networks an interesting subject for research. This interest is magnified in the context of innovation in biotech since university labs play a crucial role in licensing technology to start-ups and large firms (as mentioned before). Typically several large companies engage in research alliances with top schools and the outcomes of this study should help in structuring the network of alliances. In addition, the subject has technology policy implications on how national funding agencies and university administrations should help engender and support these networks in academia and national labs.

Commercial Outcomes

The biotech industry witnesses the creation and extinction of several start-ups each year. While the venture capital industry specializes in 'picking the winners' from scores of new ideas/concepts thus lowering the odds of failure, the high level of uncertainty prevailing over a nascent technology ensures that its hard to predict success. Thus it has become popular to devise surrogate measures to try and predict *apriori*, the probability of commercial success of a new venture. This study delves into what are being widely considered as crucial ingredients for commercial success and their drivers.

CHAPTER 2: LITERATURE REVIEW

Research Networks

Research networks are considered to be extremely crucial for success in the biotechnology arena (Powell 1996). Start-ups dominate the biotechnology industry and thus it is not uncommon to witness a large number of alliances between them and large pharmaceutical companies. These alliances have invited attention from researchers, especially sociologists. Researchers have postulated that network composition has great bearing on the performance of start up biotech companies (Baum et al 2000). They also talk about how the network should be efficient and should eliminate non-redundancies (Burt 1992). The position of firms within a network is also a crucial dimension in its collaborative research success (Powell 1996). To fully leverage the benefits of a research network, firms need to occupy a central position in the network, i.e. they should maximize the number of contacts with other members of the network, directly or through structural equivalence. This is shown to positively affect sales growth as well as the ability to forge more research ties in the future.

This section of the thesis deals with the specific areas of **collaboration and its benefits**, and **nature of ties among network participants** and its impact on the research output of the partners. Scientific collaboration has long been accepted as being important for research productivity. Some of the earliest studies have been done on Nobel laureates and how they are more collaborative and more productive than others (Zuckerman, 1967). Collaborations are said to be useful for several reasons. Many times, collaborations leverage the use of expensive equipment, which makes the research feasible (joint sharing of costs and extracting value from the purchase) (Meadows, 1974). The increased incidence of inter-disciplinary research also brings in collaborators with differing unique expertise, which contributes to research efforts (Goffman and Warren, 1980). It is also believed that tacit knowledge is best conveyed through a collaboration (Beaver, 2001). However despite such universal agreements on the benefits of collaboration, there have been few studies that have proved that collaborations do indeed enhance research output. This thesis aims to explore two issues related to collaboration quantitatively – impact of collaboration on research productivity and what kinds of collaborators (from academia/industry, etc) are more useful.

The type of research ties between collaborators has also elicited considerable interest. Network theorists (Burt 1992 and Granovetter 1973) argued for weak ties amongst players in a network. The idea proposed is that networks are constructed for players to exchange information since players have finite time on their hands to maintain their network, they should optimize it to maximize their return on social capital investment. The central tenets of this theory are those of structural equivalence and non-redundancy. Structural equivalence means that two players can extract information from each other even if they are not directly connected, if they are connected through a common network partner (some sort of a transitive relationship). Redundancy of contacts occurs if two players are connected to each other through multiple ways (direct and/or other transitive relationships). Thus it can be derived that, there is no marginal benefit of additional ties with entities that are already connected to the protagonist. It is further assumed that each tie costs effort to maintain and thus such investments should only be made into those networks where the protagonist does not have existing relationships. Information is treated like a commodity that can be easily shared (some sort of a transactional relationship) and thus tie strength is not an important element in the consideration of transmission. The theory further states that an optimal network design can be engineered by maximizing total unique information (benefit) and minimizing the cost (tie-maintenance). Assuming that people have finite time to invest, this would posit multiple ties with several groups of players with low redundancies and also argues against strong ties with any player. The argument on tie strength is based on the assumption tie strength has no bearing on the quantity and quality of information that is being transmitted.

While other network researchers have broadly accepted this theory, the context of its usage has not been defined completely. It is unclear if all kinds of collaborations involve only transactional relationships. Thus there is a body of research that believes that "search problems" in R&D would benefit from weak ties, while intensive R&D collaborations ("transfer problems") that exchange tacit knowledge requires strong ties (Hansen 1999). The main idea was to split collaborations into transactions-based and those involving transfers of complex knowledge. Transactional relationships benefit from weak ties whereas sharing of complex knowledge favors stronger ties.

"Findings show that weak inter-unit ties help a project team search for useful knowledge in other sub-units but impede the transfer of complex knowledge, which tends to require a strong tie between the two parties for a transfer. Having weak inter-unit ties speeds up projects when knowledge is not complex, but slows them down when the knowledge to be transferred is highly complex" .

This study was based on R&D projects outcomes within a company. Other than this, there have been few studies exploring what kind of ties are more productive in collaborative R&D networks. This problem is relevant to both companies as well as university researchers. Building research networks takes considerable time and energy and could have fairly long gestation periods to start producing results. Thus planning for it at the beginning would be more efficient than expensive mid-course corrections, especially when it's not easy to terminate relationships. Companies, especially in the biotechnology arena are investing into creating R&D alliances to improve their research output and they would be keen to understand a means of an efficient deployment of their funds. Scientists in academia too are measured on the quality and quantity of their research outcomes and would be interested in selecting research partners. Thus it is interesting to study how patterns of research networks impact research productivity and quality, so that scientists and institutions can take the results into considerations while drawing up their plans on collaborations.

Commercial Outcomes

This section of the thesis focuses on the relative impact of **the status** of the inventor and the quality of his/her invention on the ability of the start-up firm to attain **commercial success**. To attain commercial success, start-ups should begin by being able to raise money from investors, recruit talent to run the company, and set up oversight boards to ensure they are on track. It is then expected to develop the commercial expertise to sell the product directly or through alliances. Thus, traditional measures used in literature to size-up start-ups were focused on assets, like the patent portfolio (Henderson and Cockburn, 1994) or strategic alliances.

However, of late, innovation researchers have also published extensively using status variables in explain commercial success. This is especially true in the early life stage of start-up biotechs when there is little public information about them. Signaling is seen as important economic device, given the great uncertainty surrounding early stage biotechs. In a similar vein, the importance of collaborating with "star scientists" (Zucker et al 1996) has been shown to have a positive impact on the quantum of research output as well as the speed of commercialization of the products.

Stuart et al (1999) argued about how inter-organizational endorsements are crucial for the success of young biotech start-ups. The central hypothesis is that those start-up companies which have alliances with prominent partners, suppliers, customers or research scientists are believed to have been endorsed by these high status partners as being of high quality. These endorsements have been shown to have positive effects on the speed of the firms going IPO (Initial Public Offering) and also the their initial market valuation, controlling for other variables. These two outcome parameters have been studies, as they are key milestones for the venture capitalists funding these companies.

Higgins and Gulati (2003) studied the impact of the reputation of the senior management team and board of directors on the prestige of the underwriting bank that took the start-up to an IPO. The premise of using the underwriter prestige as an outcome variable is that earlier studies (Carter and Manaster 1990) showed it to be strongly correlated to IPO success. The paper argues that, companies with senior management with previous experience at top pharmaceutical and biotech companies as well as those who have been top institutions in academia and research labs, are more likely to obtain a prestigious underwriter for their IPO process. The rationale for this hypothesis is that when reputed management and BOD members choose to work at a start-up company and thus put their careers at risk, they are sending a strong signal about the likelihood of the success of the start-up, which is valued by the outside world.

Shane and Stuart (2002) studied the impact of the endowments of the founding team on the start-up's life chances. The endowments were classified as social capital (social network access to VC firms, prior to founding the company), human capital (prior experience in the pharmaceutical/biotech industry or in another start-up) and technical capital (inventor status in a research institution and the strength of the patent portfolio). The findings show that these endowments have a positive impact on the ability to obtain VC financing, go IPO and whether failed or succeeded finally.

A survey of this literature helps us in arriving at two conclusions, which form the basis for this section of thesis. There is evidence to suggest that reputed management teams, BOD members, SAB members and prominent VCs are all good predictors of the eventual commercial success of start-ups. There is lesser clarity on the core factors that might have contributed in bringing together these crucial elements. Inventor reputation has been shown to be important, however the impact of the reputation of the research idea itself is unknown. Thus this thesis focuses on the relative impact of these two reputation variables on commercial success.

CHAPTER 3: THEORY PROPOSED

Research Networks

As mentioned earlier, this section of the thesis is interested in exploring the benefits of collaboration and the nature of ties with research collaborators. Harriet Zuckerman's work on Nobel laureates (1967) argued that they tended to collaborate more and also produced more research output than their peers. Network theorists would also agree that more non-redundant ties to distinct partners would yield more returns. This can lead us to believe that more external (from other institutions) research collaborators would yield higher research output. This can be supported by several possible reasons; greater degree of cross-pollination between different labs, better division of labor, justification of the alliance among others.

Hypothesis 1: The greater the number of external research collaborators, the greater would be the research productivity of the scientist involved.

We can believe that research involves both tacit as well as sharing of complex knowledge (Hansen, 1999), and thus successful research would require strong ties between the various collaborators. There are two ideas embedded here; one is that of stronger ties are required for the transmission of complex knowledge and second that of one-off research associations may not necessarily lead to the benefits of collaboration mentioned above (greater cross-pollination of ideas and division of labor).

Hypothesis 2: The greater the tie strength with external collaborators, the greater would be the research productivity of the scientist involved.

However once a strong tie is established with a research partner the marginal utility of continued collaboration may taper off after a while. This is in-line with the arguments of network theorists who prefer multiple ties with different partners rather than concentrated efforts with a few. This is an especially difficult problem to resolve in the scientific world as scientists do have their favored collaborators with whom they might develop friendships and comfort working together. Its non-intuitive to believe that such continued collaboration is at the risk of more ideas that can germinate from other relationships.

Hypothesis 3: The greater the concentration of ties with some external collaborators, the lesser would be the research productivity of the scientist involved.

Commercial Outcomes

As mentioned before, this section of the thesis explores the relative impact of the reputation of the inventor and the quality of his/her invention on the ability of the start-up firm to assemble a reputed management team, board of directors, scientific advisory board and a well networked venture capitalist. Stuart's work on inter-organizational endorsements (1999), argued for the importance of signaling for biotech start-ups. Drawing from this work, we can propose that the presence of a famous inventor is likely to catalyze the constitution of a reputed team for the start up.

Hypothesis 1: The greater the reputation of the inventor, the greater would be the organization's ability to assemble a more reputed team.

Often times, the publication of a new technology in prestigious journals like Science or Nature, and its acceptance in the broader scientific community, confers reputation upon the idea. It's not uncommon to for scientists to use this reputation to find sources of funding (by sending a signal to investors that the idea has been vetted by the scientific community) for their commercialization and assemble a management team.

Hypothesis 2: The greater the reputation of the research idea, the greater would be the organization's ability to assemble a more reputed team.

The importance of signaling in biotech start-ups is largely driven by the high level of uncertainty about the viability of the underlying technologies. Thus to the outside world (and investors), the association of famous names with that start-up inspire confidence to invest (Stuart et al, 1999). Thus, it is plausible to argue that reputation effects of either the inventor or the research idea are the most when there is greater underlying uncertainty about either.

Hypothesis 3: The greater the reputation of the inventor, the greater would be the organization's ability to assemble a more reputed team, when the underlying research idea is not highly reputed.

Hypothesis 4: The greater the reputation of the research idea, the greater would be the organization's ability to assemble a more reputed team, when the inventor is not highly reputed.

Similarly, using the same rationale, we can argue that when there is more clarity about the reputation of either the inventor or the research idea, the reputation effects are lower.

Hypothesis 5: The reputation of the inventor has no impact on the organization's ability to assemble a reputed team, when the underlying research idea is highly reputed.

Hypothesis 6: The reputation of the research idea has no impact on the organization's ability to assemble reputed team, when the inventor is highly reputed.

CHAPTER 4: RESEARCH NETWORKS STUDY

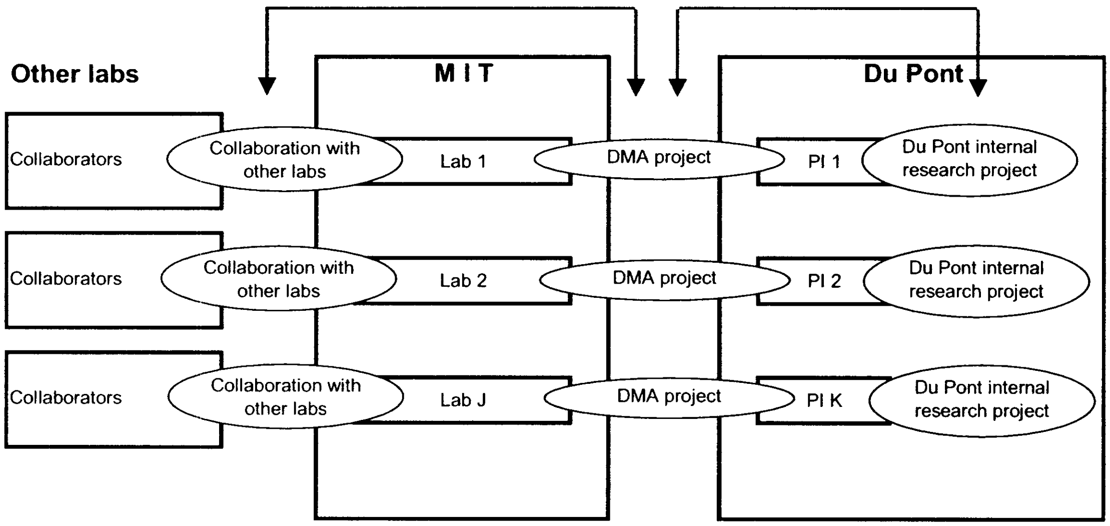
Research Design

Study Setting: The Du Pont – MIT Alliance

Du Pont is in the process of re-inventing itself as a life sciences company after a century of focus on chemistry. A significant component of this thrust is to focus on biological sciences, which promise to deliver the next wave of innovation in several areas including biomaterials. Thus Du Pont, like many large corporations faces the challenge of transforming its scientific expertise and also being successful in commercially deploying the same. While Du Pont has already made forays into Crop Sciences (through genetically modified seeds) and ran a pharmaceuticals division for a short period in the past, its entry into biomaterials is just taking place. Du Pont has created a separate venture called Bio-based Materials to ensure that it does not conflict with its existing materials business, which is the chief revenue generator for the company. In an effort to develop a "character changing" relationship with MIT, Du Pont and MIT have entered into a long-term research alliance to help advance its research capabilities in the area of biotechnology, specifically in biomaterials.

The alliance has been in place for the past 3 years and its success is of considerable interest to both parties. The DMA offers a unique opportunity to study and compare the research collaborative patterns of two types of entities. These are a) university tie-ups of large companies as represented by the DMA projects and b) R&D in large firms as represented by the internal projects of Du Pont. This arrangement would control for behavioral characteristics (e.g. proclivity to publish, initiative to see the idea through to commercialization, etc) of the scientists involved. For the specific purposes of this thesis, the research output of the MIT and Du Pont scientists involved in the DMA have been chosen as the subjects.

Figure 3: Research design schematic – Research networks



Data Collection Method

The principal subjects for analysis are the Principal Investigators (PIs) from MIT and Du Pont funded by the Du Pont MIT Alliance (DMA). DMA funds projects through a Steering Committee that screens project proposals. The Steering Committee also reviews project progress periodically through poster presentations located both at MIT and at Du Pont. MIT scientists have also received Du Pont senior management team attention on several occasions. Typical projects have one or many MIT faculty with a Du Pont scientist in the role of a liaison with the company. The Du Pont scientists (the words scientists and PIs will be used interchangeably from here onwards) are from the company's Central Research and Development Experimental Station at Wilmington, Delaware. A total of 11 Du Pont PIs are associated directly with the DMA. This research centre is well reputed and has recently celebrated 100 years of existence. MIT scientists are from 11 engineering and science departments varying from Physics to Bioengineering to Brain and Cognitive Science. These PIs include a mix of highly distinguished scientists, well reputed in their fields to young faculty who have recently joined MIT. Their commonality however is a research interest in biotechnology. A total of 40 MIT PIs are associated with the DMA.

Secondary data has been the primary source for the analysis. The limitations of using secondary data include not being the accurate representation of the actual time spent by the researcher with various researchers. The other issue is that of identity of the collaborators. Several research arrangements may not necessarily result in publications (like license agreements, etc) and thus would not be captured with outcomes based measurements. Thus it would be useful to conduct a primary survey with all the researchers in addition to secondary data. This was not conducted for this thesis, due to shortage of time. The following secondary data was gathered for all the PIs:

1. Data on all journal articles published from 1973
2. All issued patents as well as patent applications from 1976

The publications data was sourced from Web of Science (to maintain consistency). This database maintains records from 1973. Only MIT based publications of MIT PIs (they could have been publishing other places they were graduate students, post docs or faculty) were considered to control for the environment. The patents related data was sourced from the US Patents Office. This database is organized by author, assignee and other search fields only from the time period 1976 onwards. Additional data collected included the publicly available information on the relationships between MIT PIs and companies (both start up and established companies). The nature of the relationships list included being on the Scientific Advisory Board, Board of Directors, founding members, licensing arrangements, etc.

All the publications were classified based on the collaborative nature of the work. This classification was undertaken based on the address fields listed for each publication. MIT PIs' publications were classified as follows:

- Department (if all the co-authors were from the same department as the PI)
- MIT (if all the co-authors included scientists from other departments at MIT)
- Other university lab (if one of the co-authors is from a non-MIT university lab)

- National Labs (if one of the co-authors included a scientist from a National Lab)
- Industry (if one of the co-authors is from any company)
- Hospital (if one of the co-author is from a Hospital)

In case of conflicts (if a publication met more than one of the above criteria), the priority sequence was Industry, Hospital, National Lab and Other University Labs. The reason being, the incidence of these occurrences is low (in that sequence) and thus the priority sequence to capture as many as possible. However for the sake of computing total number of collaborators from any category, all instances were considered (a National Lab collaborator would be counted from a publication, even if the publication's classification was "Industry"). The publications of Du Pont PIs were similarly classified as "Du Pont" (within Du Pont), "University" (with academia), "National Labs" (with National Labs) and "Industry" (with other companies).

Dependent and Independent Variables

<u>Dependent variables</u>

Research productivity: Research productivity was measured as the average number of publications per year during the active publishing period (between the first recorded publication year and the most recent one). There are several ways to measure productivity. This measure is different from several methods used by various researchers. Other methods try to either give full credit only to the first author, or equal credit to all authors by dividing the credit of a publication amongst all the co-authors. However there are still theoretical limitations of such methods such as, alphabetical listing of authors which can work against them, listing of "honorary authors" for social reasons, etc. In additional to theoretical reasons, practical reasons include the improper listing of all authors (I have personally detected errors in the database where co-authors have been excluded, when cross-verified with other sources). Thus there is no easy way of the complex issue of attributing the "appropriate credit" of a publication to an author. Previous research (Zuckerman, 1967) also shows how the disputes regarding according the "correct amount" of credit for research extend to the level of a Nobel Prize.

Research quality: Research quality was measured as the average number of forward citations of the top three cited publications of a scientist. This is meant to be an indication of the research quality and thus how widely accepted in the field. The limitations of this measure include the following; no control for extent of self-citing, no control for the prestige of the journal in which the article is published. However, it is reasonable to assume that high status journal articles are cited more, because of some association of quality and thus it may not be difficult to make the leap that the bar is correspondingly high.

Independent variables

Breadth of links: The breadth of research links was measured as the number of distinct collaborators per scientist, classified by category. The categories considered for MIT PIs are other University labs and Industry. As mentioned earlier, the count of the number of collaborators includes all distinct labs regardless of the classification of the publication. Breadth of ties is used as a surrogate to measure reach of the scientist into other research networks. The limitation of this measure is, it does not give an accurate representation of the number of "active" research links, which is more likely to have a relation to research productivity. The other limitation is the lack of a measure for "structural equivalence" and "redundancy".

Strength of links: The strength of research links was measured as the average number of publications with a research collaborator within a category, per scientist. Thus if a scientist published 30 articles with "Industry" and he/she has 10 Industry collaborators, the average tie strength is computed as 3. Strength of ties is used as a measure of the depth of research relationships. The limitation of this measure is that, it ignores the skew in research relationships (many publications with some collaborators and one-off publications with others).

Concentration of links: The concentration of research links was measured as the skew in research publications within a category with the lead collaborator. Using the same example from above, if a scientist published 30 articles with "Industry" and 21 of those with the same company, concentration is computed as 70%. This measure is used to estimate the level of decreasing marginal utility of collaboration with a single research partner.

Method of Analysis

The statistical method used is OLS regression. The analysis was done separately for MIT PIs and Du Pont PIs. Hypothesis 1 was tested by regressing research productivity with two variables, one at a time; the number of university collaborators and the number of industry collaborators. MIT PIs were regressed with non-MIT university collaborators and the number of industry collaborators. Du Pont PIs were regressed with number of university collaborators (weak interactions with other industry labs). In addition to testing for research productivity as a dependent variable, I also tested for research quality as an outcome variable, with the research productivity. The reason for doing so was to estimate the degree of correlation between higher productivity with being well accepted in the field. In some sense, it is to check of research productivity is a good measure of "quality".

Hypothesis 2 was tested by regressing research productivity with strength of ties variables. Similarly, Hypothesis 3 was tested using the concentration of ties variables. In addition to these analyses, further analyses were conducted. A scientist's time can be used to either publish or produce patents. There is a common discussion on whether they are competing elements or complementary in nature. This is especially true for Du Pont PIs since there could potentially be higher pressure in industry to produce patents as opposed to publish articles. Thus a regression was conducted to measure estimate the correlation between research productivity and patent productivity (number of patents/patent applications per year). In addition, the overall research collaboration of Du Pont Central R&D was analyzed (on lines of Du Pont PIs). This analysis was done to gather additional insight into the functioning of Du Pont Central R&D, as the number of Du Pont PIs were limited (11).

Results

I will discuss some summary research statistics initially that will set the context for the broader discussion on the analysis of the hypotheses (see Appendix 1 for sample data). The overall pattern of publications of MIT and Du Pont appears similar (see Figure 4). There is a marked majority of publications that are with in-house collaborators, (MIT for MIT PIs and Du Pont for Du Pont PIs). However there is a dramatic difference in the levels of output (see Figure 5) in terms of number of publications per scientists, research productivity, patent productivity, etc. The difference, among other things appears to be in the number of collaborators seen in the same figure.

Figure 4: Patterns of publications

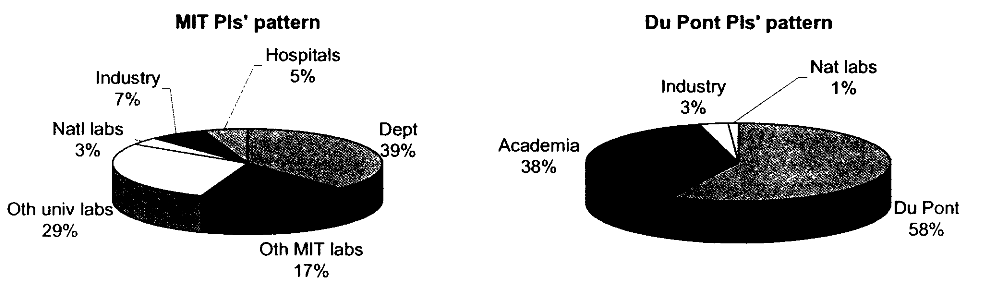
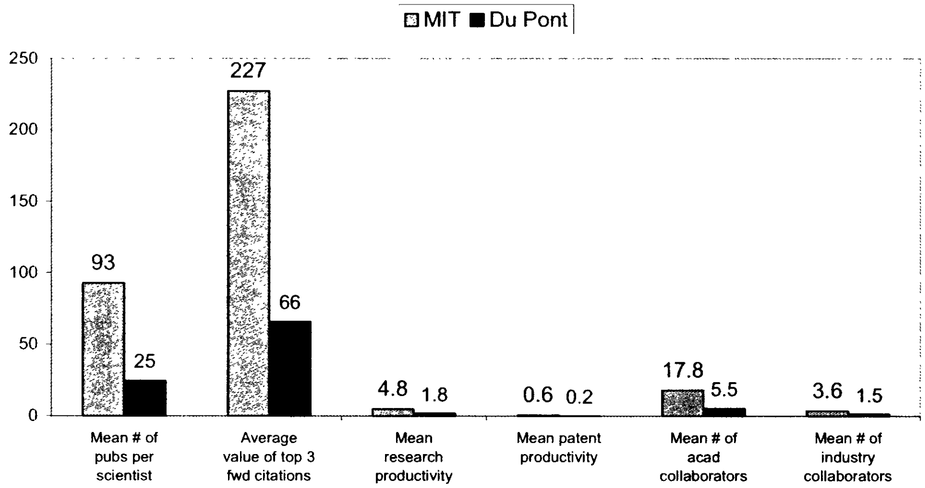
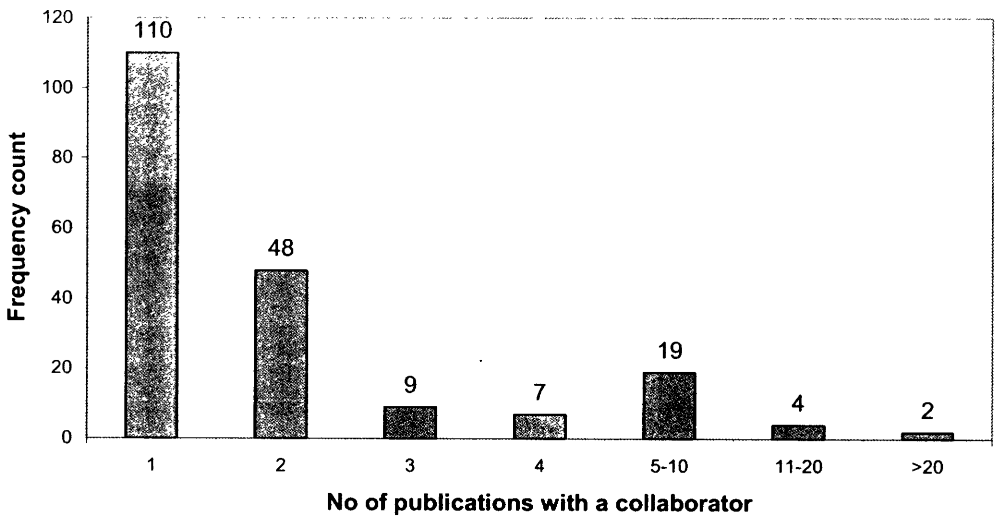


Figure 5: Brief research statistics of MIT and Du Pont PIs



The research pattern of Du Pont Central R&D was found to be broadly similar to the data on the PIs. Joint research with Academia accounts for over 50% of the research work done at the Experimental Station. They have had over 200 distinct university labs as collaborators over the last 6 years. However the relationships appear to be one-off than strong ties with a number of universities (see Figure 6).

Figure 6: Du Pont Central R&D's research ties



The test for breadth of ties' impact on research productivity revealed a strong correlation between number of collaborators and research productivity in line with Hypothesis 1. MIT PIs' research productivity had a strong positive correlation with the number of non-MIT university collaborators (see Figure 7). The regression equations, r squares values and t-test results are as under. The y-values are research productivity and x-values are the number of collaborators:

MIT PIs – Number of non-MIT university collaborators:

$Y = 0.1406X + 2.3291$; $R^2 = 0.8015$ (t value significant at $p < 1\%$)

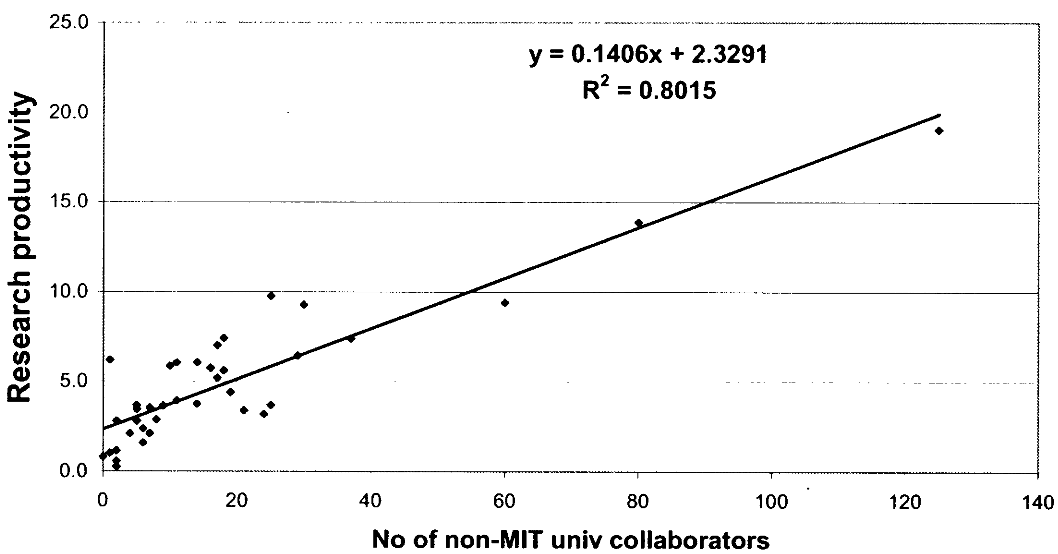
MIT PIs – Number of industry collaborators:

$Y = 0.6998X + 2.3181$; $R^2 = 0.6197$ (t value significant at $p < 1\%$)

Du Pont PIs – Number of University collaborators:

$Y = 0.0963X + 1.283$; $R^2 = 0.2662$ (t value significant at $p < 5\%$)

Figure 7: Breadth of ties – MIT PIs with non-MIT university labs



The test for strength of ties' impact on research productivity revealed a weak correlation between strength of ties and research productivity. This could mean either Hypothesis 2 is incorrect or the measure for tie strength has to be modified (see earlier discussion of variables). MIT PIs' research productivity had a positive correlation with the strength of ties with non-MIT university collaborators (see Figure 8), but the other correlations were quite weak. The regression equations, r squares values and t-test results are as under. The y-values are research productivity and x-values are the strength of ties:

MIT PIs – Strength of ties with non-MIT university collaborators:

$Y = 3.4376X + 0.5006$; $R^2 = 0.2452$ (t value significant at $p < 1\%$)

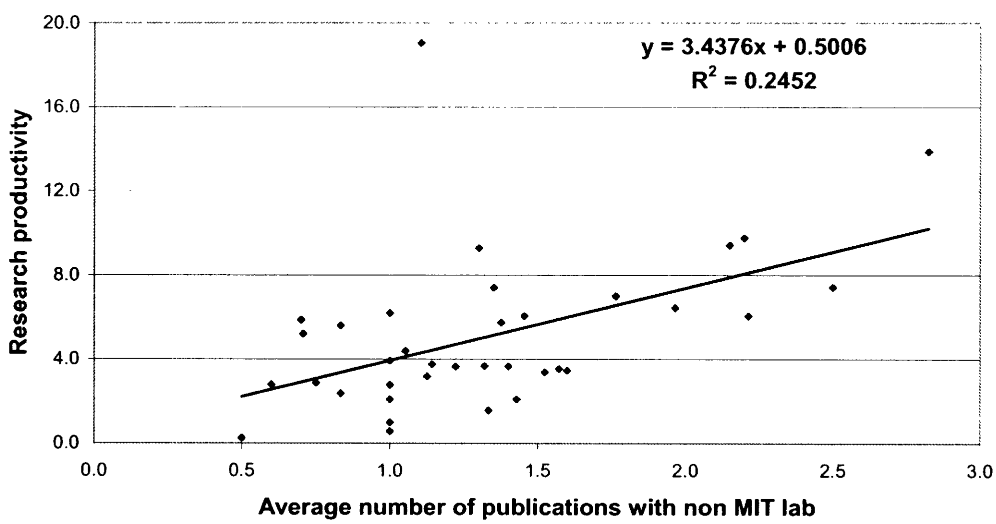
MIT PIs – Strength of ties with industry collaborators:

$Y = 0.5217X + 4.7603$; $R^2 = 0.0288$ (t value not significant)

Du Pont PIs – Strength of ties with University collaborators:

$Y = 0.0881X + 1.7155$; $R^2 = 0.0354$ (t value not significant)

Figure 8: Strength of ties – MIT PIs with non-MIT university labs



The test for concentration of ties' impact on research productivity revealed a mild negative correlation between strength of ties and research productivity. The direction of the results is in line with Hypothesis 3, though the values are not substantial. MIT PIs' research productivity had a negative correlation with the concentration of ties with industry collaborators (see Figure 9), but the other correlations were quite weak. The regression equations, r squares values and t-test results are as under. The y-values are research productivity and x-values are the concentration of ties:

MIT PIs – Concentration of ties with non-MIT university collaborators:

$Y = -4.3045X + 6.8827$; $R^2 = 0.0944$ (t value significant at $p < 1\%$)

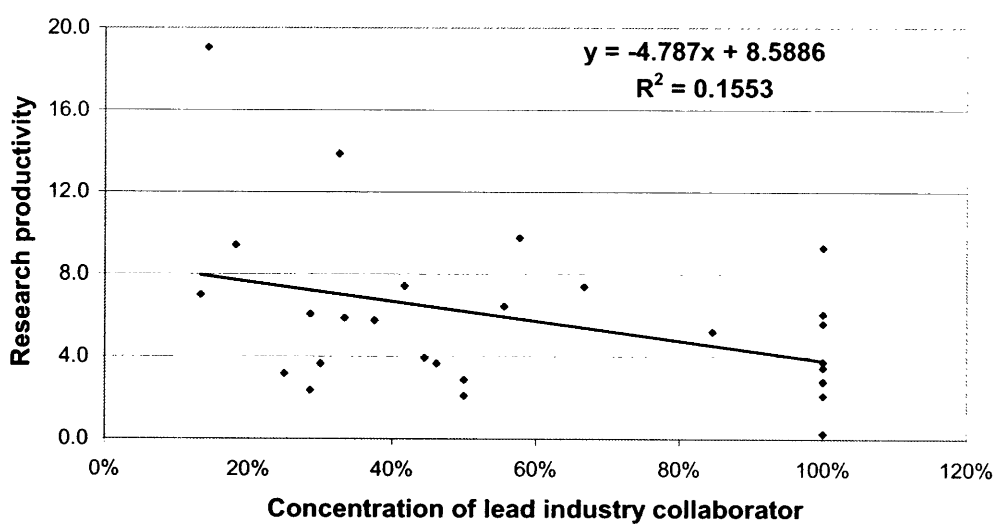
MIT PIs – Concentration of ties with industry collaborators:

$Y = -4.787X + 8.5886$; $R^2 = 0.1553$ (t value not significant)

Du Pont PIs – Concentration of ties with University collaborators:

$Y = -0.4373X + 2.1285$; $R^2 = 0.0237$ (t value not significant)

Figure 9: Concentration of ties – MIT PIs with non-MIT university labs



In addition to the above analysis, two additional analyses were conducted to test 1) the relationship between patent productivity and publications productivity and 2) the relationship between research productivity and research quality.

The analysis indicated that publications productivity and patent productivity are positively but mildly correlated (the analysis for Du Pont PIs was replaced with Du Pont Central R&D as the patent productivity values of Du Pont PIs were insignificant). This can lead us to believe that these both research activities are complementary in nature. The significance of this result is that using publications productivity as a measure of research output maybe reasonable. The regression equations, r squares values and t-test results are as under. The y-values are patent productivity and x-values are research productivity.

MIT PIs:

$Y = 0.1918X - 0.3063$; $R^2 = 0.3728$ (t value not significant)

Du Pont Central R&D:

$Y = 0.9014X + 259.11$; $R^2 = 0.3555$ (t value significant at $p < 5\%$)

The analysis indicated that research productivity and research quality are positively but weakly correlated. The significance of this result is that those scientists that publish more are also likely to be cited more. This is similar to the finding that Nobel laureates (who are among the most reputed in their field) also are amongst the most productive (Zuckerman, 1967). The regression equations, r squares values and t-test results are as under. The y-values are research quality and x-values are research productivity.

MIT PIs:

$Y = 35.887X + 53.941$; $R^2 = 0.1228$ (t value significant at $p < 5\%$)

Du Pont PIs:

$Y = 18.759X + 32.125$; $R^2 = 0.081$ (t value not significant)

CHAPTER 5: COMMERCIAL OUTCOMES STUDY

Research Design

The Du Pont-MIT Alliance was well suited for a study on research networks, and should have ideally been used for the study on commercial outcomes. However, it could not be persisted with it due to study sample limitations - few research concepts emerging from the alliance are ready for commercialization. Thus a new research setting was selected.

Study Setting: The Biotechnology sector in Massachusetts

The biotech industry in the US is largely concentrated in geographical clusters. The leading clusters are in California and Massachusetts and the New England area. The availability of a large pool of scientific talent is a necessary pre-condition to the creation and sustenance of these clusters. A recent study stated that there are about five thousand scientists working in life sciences, in the Massachusetts area. There are about thirteen institutions offering higher education in life sciences. This pool of human resources has proven to be a happy hunting ground for biotech start-ups. This region has attracted over $2 billion in venture capital investment as well as receives $1.5 billion in funding from the NIH (National Institute of Health) every year. This region also has witnessed increased alliances between Big-Pharma and biotech companies, resulting in $3.9 billion dollars in alliance value since 1996 (The Brookings Institution Report, 2002).

It is estimated that there are about 400 biotech companies in the Massachusetts area. These companies have their origins in university labs (through technology transfer), large pharmaceutical and biotech companies and research laboratories. 150 of these companies have their research origins in technology transfers from universities. Technology transfers from MIT, Harvard University and Boston University account for a majority (over 50%) of all the biotech companies founded in Massachusetts. These universities continue to be the major contributors of scientific talent and ideas to companies in the region.

The biotechnology sector in Massachusetts, with its high rate of firm creation, an active venture capital community and an extensive university – industry collaboration, lends itself to an excellent subject for the study on commercial outcomes. This region has its fair share of both successful and failed ventures, technology tie-ups with both reputed and middle rung universities and access to both reputed and smaller venture capitalists. This large variation across various dimensions as well the presence of a large number of firms provides for the construction of statistically valid study and control samples to test several hypotheses.

Data Collection Method

The sample chosen for the study was all the biotech firms based out of Massachusetts, started after 1995. The reason a cut-off date was chosen due to difficulty in gathering the following data on older companies: 1) venture financing and founders 2) failed ventures. Another selection variable for the data was choosing only therapeutics and medical product companies. Several contract research organizations, contract manufacturers, diagnostics and imaging companies commonly listed under biotechs, were all dropped from the sample set. A total of 209 Massachusetts based biotech start-ups, started after 1995, were selected as the final sample set.

Secondary data was the primary source for the analysis. The data on which companies to select was chosen from the following databases, Massachusetts Biotech Council (MBC) directories (2000 and 2003), VentureXpert database (Thomson Financial), Boston Business Journal, GEN database and Bioscan. Together these databases cover extensively, names of most biotech start-ups in the Massachusetts area. These names were then cross-referenced from data sources on the Internet for their business model (therapeutics/CRO, etc) and their start date, to select the sample set. Once the sample set was selected, the following information was gathered on each company:

- The names and qualifications of the founding senior management team (includes CEO, COO, CSO (Chief Scientific Officer), Head of Research and Head of Business Development)
- The names and qualifications of all the Board of Directors
- The names and qualifications of all the members of the Scientific Advisory Board (SAB)
- All the venture capitalists who invested in the venture
- The starting scientific idea/technology on which the company was built
- The name and qualifications of the scientific founder/inventor
- Whether the invention was originated in a university lab, and if so which one

In addition, financial data and a list of portfolio companies was collected for all the venture capital firms that were associated with these companies: The following sources were used to collect data on the companies and venture capital firms:

- Company websites and other sources like www.biospace.com
- VentureXpert (Thomson Financial)
- Web of Science - for all journal publications
- USPTO (Patents office) – for all patent related data

After the extensive data search, the sample set reduced to 111 companies. 59 companies dropped out for having no/limited overall information and 39 dropped due to lack of information on their scientific origins.

Dependent and Independent Variables

<u>Dependent variables</u>

Reputation of the management team: Each of the senior management team members was scored using a binary variable based on whether they worked previously at one or more of the following: 1) Top 15 pharma company (by sales) 2) Top 10 biotech company (by sales) and 3) as a Faculty member at a top 10 school in their department. Higgins and Gulati (2003) used similar measures to value the management experience of senior management at entrepreneurial biotech firms. The pharma and biotech sales rank was based on 2002 figures and was crosschecked across multiple sources to verify the authenticity. School rankings by department were obtained from two sources, US News Graduate School Rankings (quoted by MIT to report their standing) and the Gourman Report (used by Higgins and Gulati (2003)). These binary scores were summed up for each management team member (with a range of 0 to 3 of possible scores). Two sub-variables were computed to measure management team reputation:

1. Management team total score: Total score for the company, across all management team members
2. Management team average score: Average score for the company (total score divided by total number of management team members)

Reputation of the members of the Board of Directors (BOD): The same methodology as above was employed to compute two sub-variables (similar to above):

1. BOD total score: Total score for the company, across all BOD members
2. BOD average score: Average score for the company (total score divided by total number of BOD members)

Reputation of the members of the Scientific Advisory Board (SAB): Each of the SAB members was scored using a binary variable based on whether they were any of the following: 1) Nobel Laureate 2)

Member of any of the three Academies (Science, Engineering or Medicine) and 3) Faculty member at a top 10 school in their department. Audretsch and Stephan (1996) used similar measures to value expertise of SABs. If a scientist is a member of more than one Academy, additional score is recorded (2 for two memberships and 3 for three memberships), as each membership carries its own prestige. School rankings by department were obtained from two sources, as above, US News Graduate School Rankings. These binary scores were summed up for each SAB team member (with a range of 0 to 5 of possible scores). Two sub-variables were computed to measure SAB reputation:

1. SAB total score: Total score for the company, across all SAB members
2. SAB average score: Average score for the company (total score divided by total number of SAB members)

Commercial prominence of the Venture Capital firms: The following data was collected on all the venture capital firms that were associated with each company: 1) Total sum under investment ($ million), 2) Number of biotech ventures they have invested in and 3) Sum invested in biotech ventures ($ million). Stuart, Hoang and Hybels (1999) used similar measures to measure the prestige of venture capital firms. In an attempt to unify the measurement variables, the number of biotech ventures and sum invested in biotech ventures by venture firms were regressed against each other. The resulting R square was 85%, prompting the usage of number of biotech ventures as the single variable to measure commercial prominence. The raw scores of each VC firm were broken up into ranges (5, 10, 20, 40, and greater than 40) and scored on a 1-5 scale. Two sub-variables were computed for each company:

1. VC total score: Total scores for the company, across all its VC firms
2. VC average score: Average score for the company (total VC score divided by total number of VCs)

Independent variables

Idea quality: Two sets of data were collected for each company, on the founding scientific idea – the relevant patent(s) and journal publication(s) along with their forward citations count. A patent raw score was computed for each company, based on the number of forward citations of the leading patent. Stuart, Hoang and Hybels (1999) used similar measures to measure the technological prominence of a start-up biotech company. These raw scores were broken up into ranges (0, 5, 10, 30 and greater than 30) and scored on a 0-10 scale. Separately, a raw publication score was computed by multiplying the number of forward citations of the publication with the impact factor score (Computed by ISI Web Science for all journals, said to represent their relative reputations) of the journal it was published in. Since these raw scores had a huge variation (from 0 to 14,000), they were converted to a log scale and broken into ranges (0-10) and scored on a 1-10 scale. The patent score was eventually dropped due to two reasons: 1) minimal correlation with the publication score (0.11) and 2) no effects when correlated with other dependent variables. Thus the publication scaled score was used as a measure of Idea quality.

Inventor reputation: I used a methodology similar to the one used to measure SAB reputation, to measure inventor reputation. Each of the scientific inventors/founders was scored using a binary variable based on whether they were any of the following: 1) Nobel Laureate 2) Member of any of the three Academies (Science, Engineering or Medicine) and 3) Faculty member at a top 10 school in their department. These binary scores were summed up for each inventor (with a range of 0 to 5 of possible scores). Similar to other variables, two sub-variables (Inventor total and Inventor average) were computed to measure inventor reputation. The Inventor average score variable was eventually dropped to lack of any significant effects. Thus Inventor total score was used as a measure of Inventor reputation.

Method of Analysis

I used the t-test to check for statistical validity of the various hypotheses segmenting the sample in different ways for each hypothesis. Dependent and independent variable scores were computed for each company. Hypothesis 1 was tested by using test (companies with Inventor score of greater than or equal to 1) and control samples (companies with Inventor score of 0). The means of all the dependent variables were tested across the two samples for statistical significance using the t-test, with error significance levels of 5% and 10%. Hypothesis 2 was tested similarly with a test sample of companies with Idea quality score greater than 5 and a control sample with a score of less than or equal to 5. I also tested the sample data for impact on the dependent variable on another dimension – research origins are from high (test sample) and low prestige schools (control sample), using the same methodology.

Hypothesis 3 was tested by first constructing a sample set of all companies with an Idea score less than or equal to 5. Within this sample set, companies were split into a test sample (with an Inventor score greater than 0) and a control sample (Inventor score of 0) to test for significance in dependent variables. Hypothesis 5 was tested using a similar method – an overall sample was constructed of all companies with an Idea score greater than 5 and similar test and control samples (like for Hypothesis 3) were set up to test for statistical significance.

Hypothesis 4 was tested by first constructing a sample set of all companies with an Inventor score of 0. Within this sample set, companies were split into a test sample (with an Idea score greater than 5) and a control sample (Idea score less than or equal to 5) to test for significance in dependent variables. Hypothesis 6 was tested using a similar method – an overall sample was constructed of all companies with an Inventor score greater than 0 and similar test and control samples (like for Hypothesis 4) were set up to test for statistical significance.

Results

This section will first run through some overall statistics about the companies in the sample set before detailing the results of the hypotheses (see Appendix 2 for sample data). As stated before, the final sample size of companies analyzed was 111. The starting dates of these companies (see Figure 10) appear to have a slant towards companies that have been started recently. This might be a survivor bias for lack of information about companies that have been shut down earlier leaving behind no traces in secondary sources. This is confirmed by looking at the investment status of these companies (see Figure 11), which shows only 2 firms from the sample (of 111) have been shut down, suggesting a relatively high success rate.

Figure 10: Commercial outcomes study - Sample sorted by start dates

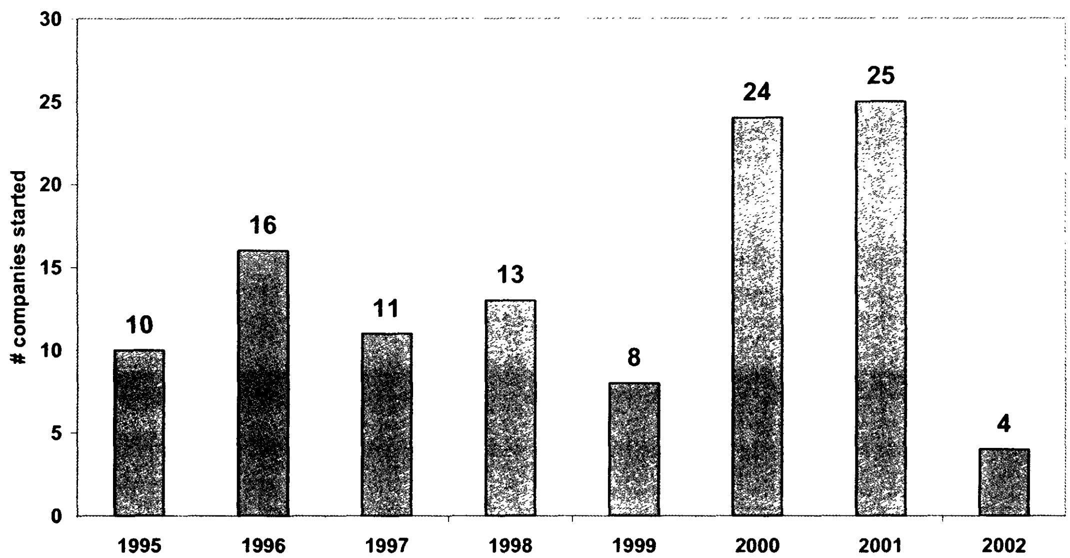
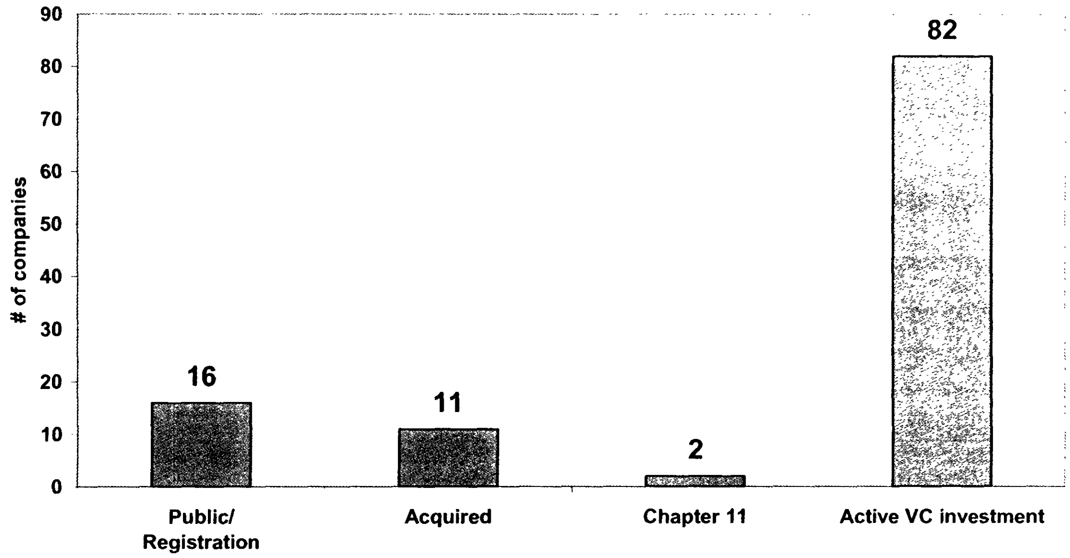


Figure 11: Commercial outcomes study - Sample's investment status



The test for inventor reputation's impact on the dependent variables revealed a strong effect through a t-test, in line with Hypothesis 1 (see Figure 12). At a broad level, higher inventor reputation for a company correlates with a more reputed management team, BOD, SAB and a more commercially prominent VC.

Figure 12: Inventor reputation impact (high vs. low)

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
All inventors										
Mean	5.5	1.2	0.4	2.5	0.4	4.2	0.9	12.3	2.5	1.5
Sigma	2.5	1.3	0.4	2.2	0.3	3.3	0.7	9.8	0.9	1.8
n	111									
High score inventors (>=1)										
Mean	6.0	1.4	0.4	2.7	0.4	5.1	1.1	12.4	2.6	2.4
Sigma	2.4	1.4	0.5	2.2	0.3	3.4	0.7	9.6	1.0	1.7
n	69									
Other inventors (=0)										
Mean	4.5	0.9	0.3	2.0	0.3	2.3	0.5	12.2	2.3	0.0
Sigma	2.3	1.2	0.4	2.0	0.3	2.1	0.4	10.1	0.7	0.0
n	42									
T value	**3.34**	**2.19**	**2.14**	**1.79**	**1.82**	**5.38**	**5.73**	**0.12**	**2.22**	**11.74**
T significant value (5%)	1.98									
T significant value (10%)	1.66									

The test for idea quality's impact on the dependent variables revealed a strong effect through a t-test, in line with Hypothesis 2 (see Figure 13). At a broad level, higher idea quality for a company correlates with a more reputed management team, BOD, SAB and a more commercially prominent VC.

Figure 13: Idea score impact (high vs. low)

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
All pubs										
Mean	5.5	1.2	0.4	2.5	0.4	4.2	0.9	12.3	2.5	1.5
Sigma	2.5	1.3	0.4	2.2	0.3	3.3	0.7	9.8	0.9	1.8
n	111									
Idea Quality (>=6)										
Mean	7.6	1.5	0.4	2.9	0.5	4.8	1.1	13.3	2.5	1.9
Sigma	1.3	1.4	0.4	2.2	0.3	3.0	0.7	10.6	0.9	1.8
n	53									
Idea Quality (<=5)										
Mean	3.5	0.9	0.3	2.0	0.3	3.5	0.7	11.2	2.5	1.1
Sigma	1.5	1.2	0.4	2.0	0.3	3.4	0.7	8.7	1.0	1.6
n	58									
T value	**15.05**	**2.20**	**1.34**	**2.33**	**2.40**	**2.15**	**2.57**	**1.15**	**-0.02**	**2.61**
T significant value (5%)	1.98									
T significant value (10%)	1.66									

As mentioned earlier, I also ran a test to check the impact of university reputation on the dependent variables. It revealed a strong effect of university reputation through a t-test (see Figure 14).

Figure 14: Impact of university reputation (high vs. low)

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
All schools										
Mean	5.5	1.2	0.4	2.5	0.4	4.2	0.9	12.3	2.5	1.5
Sigma	2.5	1.3	0.4	2.2	0.3	3.3	0.7	9.8	0.9	1.8
n	111									
High status schools										
Mean	6.0	1.5	0.5	2.8	0.4	4.8	1.1	13.0	2.6	2.2
Sigma	2.4	1.2	0.4	1.9	0.3	2.7	0.4	8.8	0.8	0.4
n	70									
Other schools										
Mean	4.5	0.7	0.2	1.9	0.3	2.8	0.5	11.3	2.3	0.2
Sigma	2.4	1.2	0.4	1.9	0.3	2.7	0.4	8.8	0.8	0.4
n	41									
T value	**3.41**	**3.25**	**3.19**	**2.23**	**2.25**	**3.73**	**6.52**	**0.98**	**2.26**	**25.77**
T significant value (5%)	1.98									
T significant value (10%)	1.66									

The test for inventor reputation's impact on the dependent variables, controlling for the underlying idea quality revealed the following outcomes:

1. No effect, when the underlying idea score is high (>=6), in line with Hypothesis 5 (see Fig. 15)
2. Strong effect when the underlying idea score is low (<=5), in line with Hypothesis 3 (see Fig. 16).

Figure 15: Impact of inventor reputation (high vs. low), given a high idea quality

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
Idea Quality (>=6)										
n	53									
High score inventors (>0)										
Mean	7.7	1.5	0.4	2.8	0.5	5.4	1.2	12.1	2.5	2.6
Sigma	1.3	1.3	0.4	2.2	0.3	3.1	0.8	10.2	1.0	1.7
n	40									
Other inventors (=0)										
Mean	7.2	1.5	0.5	3.3	0.5	3.2	0.7	16.7	2.4	0.0
Sigma	1.3	1.7	0.5	2.2	0.3	2.0	0.5	11.4	0.8	0.0
n	13									
T value	**1.12**	**-0.16**	**-0.21**	**-0.79**	**-0.43**	**3.00**	**2.76**	**-1.29**	**0.19**	
T significant value (5%)	2.01									
T significant value (10%)	1.68									

Figure 16: Impact of inventor reputation (high vs. low), given a low idea quality

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
Idea Quality (<=5)										
n	58									
High score inventors (>0)										
Mean	3.8	1.3	0.5	2.7	0.4	4.7	1.0	13.0	2.9	2.1
Sigma	1.6	1.4	0.5	2.2	0.3	3.7	0.7	8.7	1.1	1.7
n	29									
Other inventors (=0)										
Mean	3.3	0.5	0.2	1.2	0.2	1.7	0.3	9.8	2.2	0.0
Sigma	1.5	0.8	0.3	1.5	0.3	1.9	0.3	8.6	0.7	0.0
n	29									
T value	**1.21**	**2.62**	**2.54**	**3.04**	**2.32**	**3.88**	**4.99**	**1.39**	**2.97**	
T significant value (5%)	2.00									
T significant value (10%)	1.67									

The test for idea quality's impact on the dependent variables, controlling for the underlying inventor reputation revealed the following outcomes:

1. Strong effects, when the inventor reputation is low (=0) (see Fig. 17), in line with Hypothesis 4
2. No effect when the inventor reputation is high (=1) (see Fig. 18), in line with Hypothesis 6

Figure 17: Impact of idea quality (high vs. low), given a low inventor reputation

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
Low reputation inventors (=0)										
n	42									
High Idea quality (>5)										
Mean	7.2	1.5	0.5	3.3	0.5	3.2	0.7	16.7	2.4	0.0
Sigma	1.3	1.7	0.5	2.2	0.3	2.0	0.5	11.4	0.8	0.0
n	13									
Low Idea quality (<=5)										
Mean	3.3	0.5	0.2	1.2	0.2	1.7	0.3	9.8	2.2	0.0
Sigma	3.3	0.5	0.2	1.2	0.2	1.7	0.3	9.8	2.2	0.0
n	29									
T value	**5.59**	**2.16**	**2.08**	**3.30**	**3.15**	**2.35**	**2.74**	**1.87**	**0.60**	
T significant value (5%)	2.02									
T significant value (10%)	1.68									

Figure 18: Impact of idea quality (high vs. low), given a high inventor reputation

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Inv'tor sum
High reputation inventors (>0)										
n	69									
High Idea quality (>5)										
Mean	7.7	1.5	0.4	2.8	0.5	5.4	1.2	12.1	2.5	2.6
Sigma	1.3	1.3	0.4	2.2	0.3	3.1	0.8	10.2	1.0	1.7
n	40									
Low Idea quality (<=5)										
Mean	3.8	1.3	0.5	2.7	0.4	4.7	1.0	13.0	2.9	2.1
Sigma	1.6	1.4	0.5	2.2	0.3	3.7	0.7	8.7	1.1	1.7
n	29									
T value	**10.97**	**0.41**	**-0.34**	**0.11**	**0.52**	**0.91**	**1.22**	**-0.40**	**-1.58**	
T significant value (5%)	2.00									
T significant value (10%)	1.67									

CHAPTER 6: DISCUSSION AND CONCLUSIONS

Summary

The findings of this study can be summarized under the two units of analyses conducted, Research networks and Commercial Outcomes.

Research networks

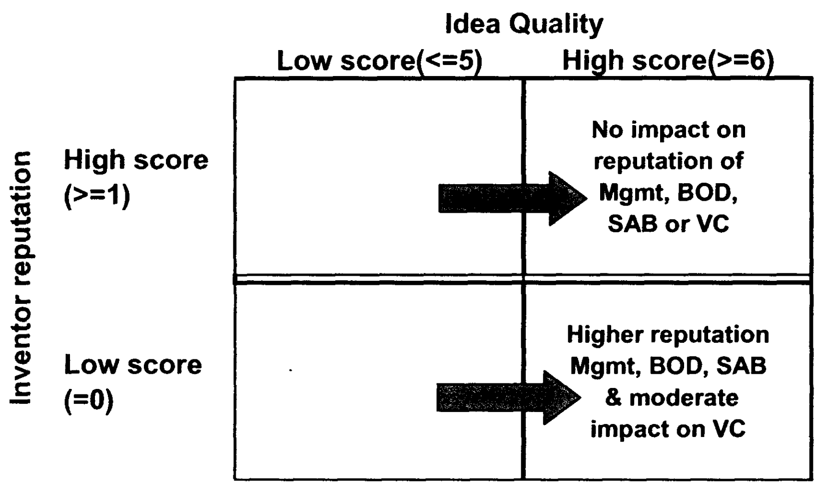
The main findings of this study are 1) larger number of collaborators from different domains increases research output, 2) stronger ties maybe more productive than weaker ties 3) concentration of ties with a few collaborators, appears to have a negative impact on productivity. The results of the analysis of Du Pont PIs are consistently statistically weak and it could be attributed to a small sample size. The potential explanations for breadth of ties could be greater degree of cross-pollination of ideas is beneficial, or an efficient division of labor amongst other possible explanations. The benefits of strong ties validate Hansen's arguments somewhat, but it appears as though multiple strong ties are considerably better than a few. This is illustrated in the research productivity of MIT PIs as opposed to Du Pont PIs and Du Pont Central R&D. The idea that concentrated ties with a few collaborators has a negative impact on productivity appears to be inline with network theorists (Burt and Granovetter) who argue against redundancy in networks and how that lowers the returns on investment. However, it can also be interpreted as, less productive researchers do not manage to get more collaborators and thus there could be a reversal of causality.

The additional findings that patent productivity and research quality variables are also closely correlated with research productivity are significant as this measure can be used in future research as a single variable to capture research output and in some essence its quality.

Commercial Outcomes

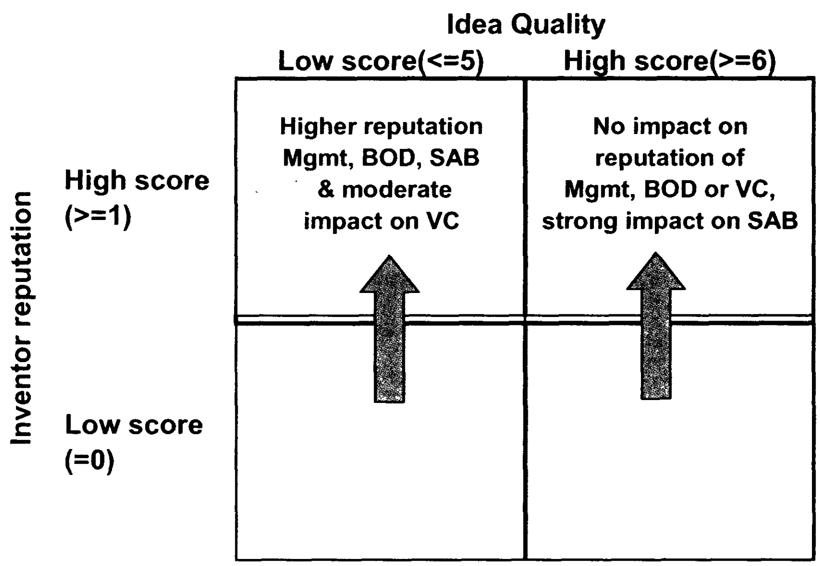
The main findings of this study are 1) higher inventor reputation augurs well for the constitution of a reputed management team, BOD and SAB as well as roping in a prominent VC firm, 2) higher idea quality has similar effects and 3) the strength of these effects is strongly correlated with the extent of underlying uncertainty. The theory to link these results can be constructed by trying to understand the process by which potential investors and employees evaluate the risk-return trade offs by investing in a relatively unknown start-up company. Thus a high reputation inventor or a highly cited technology can be seen to address some of those concerns. However it is interesting to note other effects. The analysis of the impact of idea quality, controlling for inventor reputation led to the following results. If the underlying inventor is of high repute, idea quality does not appear to make any impact on the outcome variables. However, if the inventor is of relatively low reputation, then, idea quality has a significant effect on the reputation of the Management team, BOD and SAB and to some extent on VC prominence (see Figure 19).

Figure 19: Impact of idea quality (high vs. low)



Similarly, an analysis was run for the impact of Inventor reputation, controlling for idea quality. It led to the following results. If the idea quality is high, Inventor reputation does not appear to make any impact on the outcome variables, except for SAB reputation. However, if the idea quality is relatively low, then, Inventor reputation has a significant effect on the reputation of the Management team, BOD and SAB and to some extent on VC prominence (see Figure 20).

Figure 20: Impact of inventor reputation (high vs. low)



These results reinforce the notion of the value of signaling in uncertain environments, in line with general theories in economics about the same subject. This is also broadly in line with recent sociological literature (Higgins and Gulati (2003), Stuart et al (1999), etc). However, based on the above two results, it is interesting to note that this signaling appears to work best when the underlying uncertainty is highest. Once one of the two variables (idea quality or inventor reputation) is set as "high", the effect of the other variable diminishes considerably. These effects appear to have a good promise for future testing.

Implications

This study looks at research networks and their impact on both research productivity and quality and then looks at the impact of research quality and inventor reputation on commercial outcomes. However, as seen in the research schematic (Figure 2), the process is not linear and has several feedback components to it. Research quality can enhance inventor reputation that might in-turn impact the ability to construct a different scientific network. The results also show that a scientific idea/technology, which is highly reputed, has an equivalent chance at commercial success regardless of its inventor. Implications can be drawn from these results at two levels – at the level of the technology policy and at the unit level of a firm.

Technology Policy

The results offer some pointers on how to organize university research networks and making funding allocation decisions. Broader research collaboration is beneficial to academic researchers and universities must be equipped to support such efforts. This can take the shape formally organizing networks between departments of several schools, which can facilitate collaboration as well as investing in infrastructure to support it. This can also mean, increasing the industry-academia interaction as well as with other national labs. These results also show that highly cited and quality research can emanate from schools and labs not considered to be highly reputed. This might have general implications on the decision heuristics allocating funding across schools – emphasizing on the quality of the science per se rather than the prestige of the lab associated with it.

Firm level implications

The study results send a strong signal that if a research idea is highly cited, it has the same chance at commercial success regardless of the inventor reputation. This should offer encouragement to young scientists to persist with their research and try to commercialize their science. This also shows that the commercial engine of innovation and entrepreneurship is exhibiting meritocracy to the extent possible and that augers well both for the investors as well as the economy in general.

The results also have some pointers for companies like Du Pont and other established firms trying to enter the field of biotechnology. The importance of research networks and university collaboration (with star scientists) is well documented in literature. However, ideas on the mechanism of constructing these networks are not extensive. The preliminary conclusion that can be drawn from the study is that, companies need to establish several strong ties with academia in order to boost research output. High degree of concentration with a few universities or other collaborators could be detrimental. These networks maybe have been in place for historical reasons, but efforts must be made to increase the number of strong ties.

Limitations

Research networks

The study has the following shortcomings 1) construction of variables and 2) generalizabilty of the findings. Breadth of research links variable has to be refined to include the following; accurate representation of the number of "active" research links (as opposed to total research links across al time), measures for "structural equivalence" and "redundancy". These measures are more likely to reconstruct 'real' network relationships, which are more likely to have an impact on research productivity. The strength of research links variable needs to be modified as the current variable only captures mean values and thus ignores the skewness in research relationships (many publications with some collaborators and one-off publications with others). A modal value maybe a preferred option.

The second limitation of this study is the generalizability of the results. This study was based on one university-industry research partnership. While this relationship is typical of the kind of arrangements seen on this campus and others, the results should be quoted in other contexts with adequate caution.

Commercial Outcomes

The main limitations of this study are 1) survivor bias, 2) variables construction and 3) measurement. As mentioned before, there is a likelihood that firms that could have failed may not have made it into the sample due to lack of information in secondary sources. I tried to counter this by gathering data from multiple sources across different time periods, but the bias could not be completely negated. Based on subsequent analysis with a limited sample set, the direction of the bias is unclear.

Constructing the variables has also been a challenge. Prior studies which evaluated the effects of reputation and prominence, constructed dependent or independent variables based on single binary measures (worked previously in a top 20 pharma company, faculty of a top 10 school, etc). This study used binary variables which in-turn was a summation of sub-binary variables (e.g. inventor reputation was a summation across the sub-binary variables of Nobel laureate, Member of the National Academies and Faculty member in a top 10 school). The effects of such horizontal summation on statistical significance and validity need to be further studied.

There were several challenges in measuring the variables. It would be ideal to get data on the founding management team, BOD, SAB and VC firms to rigorously test the hypotheses. However, as time progresses, in many cases, the distinction between historical and current information blurs creating accuracy challenges. Survivor bias would have a role here, as if start-up firms last longer, they signal positive results which might lead to more high status teams joining the firms thus creating measurement issues. The other challenge was in obtaining idea quality data. Many companies do not list their originating patents and publications and thus such data had to be reconstructed based on the inventor names as well as research profile of companies. This might lead to some inaccuracies. Also, a significant chunk (39 companies) of the initial sample was dropped only due to lack of data on Idea quality.

Directions for Future Research

The findings of the study offer avenues to direct future research along the following lines:

1. Refinement of the current research
2. New affiliated research problems

As discussed before, the studies on both research networks as well as commercial outcomes need to be refined in terms of sample section, the construction of variables and measurement. It is also very important to conduct primary research to supplement the findings based on secondary research. The PIs of MIT and Du Pont need to be interviewed and administered questionnaires to understand how they allocate their time. This will help us understand their pattern of collaboration and active research links. Similarly interviews need to be conducted with scientific founders of start-up companies to understand the process of how they got VC funding and assembled their teams. This will help corroborate the results from the analysis as well help in choosing appropriate variables and measurement.

While this research focused modularly on the impact of research networks, idea quality and inventor reputation, studying the interdependencies and feedback loops would offer much interest. Such problems would be in the nature of:

- How do research networks evolve over time and what are the determinants?
- The impact of research and social networks on the success of start-up ventures, and its feedback into the research network
- How can the commercialization process be speeded up, what can other firms learn from successful start-ups, in this aspect?

APPENDIX 1 – A: Research Networks Study - Summary MIT PI Sample Data

MIT PI	Total # of publications	# of industry collaborators	# of academic collaborators	Average # of publ'ns per company	Average # of publ'ns per univ lab	Conc with lead ind	Conc with lead univ	Publications/yr
Yet-Ming Chiang	84	7	9	1.4	1.2	30%	18%	3.7
Robert E Cohen	161	7	16	2.3	1.4	38%	36%	5.8
Thomas Consi	4	0	2		1.0		50%	0.6
Patrick Doyle	1	0	1		1.0		100%	1.0
Mildred Dresselhaus	430	14	80	3.1	2.8	33%	19%	13.9
Linda Griffith	45	4	5	0.5	1.6	100%	75%	3.5
Alan Grodzinsky	103	4	25	3.3	1.3	46%	27%	3.7
Alan Grossman	53	0	7		1.6		36%	3.5
Paula Hammond	39	2	2	1.5	1.0	100%	50%	2.8
T. Alan Hatton	115	1	14	6.0	2.2	100%	35%	6.1
Darrell Irvine	8	0	2					1.1
Klavs Jensen	105	9	17	1.7	1.8	13%	50%	7.0
Roger Kamm	105	0	21		1.5		69%	3.4
Robert Langer	457	16	125	1.3	1.1	14%	62%	19.0
Douglas Lauffenburger	65	1	30	1.0	1.3	100%	18%	9.3
L. Mahadevan	11	0	6		1.3		25%	1.6
Paul Matsudaira	51	4	24	1.0	1.1	25%	37%	3.2
Anne Mayes	52	3	17	4.3	0.7	85%	33%	5.2
Christine Ortiz	5	1	2	2.0	0.5	100%	100%	0.3
Rajeev Ram	22	0	5		1.4		43%	3.7
Alexander Rich	292	11	60	1.0	2.2	18%	21%	9.4
Michael Rubner	103	6	11	1.2	1.5	29%	19%	6.1
Ram Sasisekharan	56	2	18	0.5	0.8	100%	33%	5.6
Martin Schmidt	45	6	6	1.2	0.8	29%	20%	2.4
Peter Seeberger	31	0	1		1.0		100%	6.2
David Schauer	23	2	8	1.0	0.8	50%	67%	2.9
James Sherley	4	0	0					0.8
Anthony Sinskey	132	0	19		1.1		20%	4.4
Henry I. Smith	230	12	18	3.0	2.5	42%	18%	7.4
Peter Sorger	21	1	7	1.0	1.4	100%	70%	2.1
Greg Stephanopoulos	88	3	10	1.0	0.7	33%	57%	5.9
JoAnne Stubbe	103	3	29	3.0	2.0	56%	28%	6.4
Mriganka Sur	60	1	14	1.0	1.1	100%	25%	3.8
Steven Tannenbaum	222	4	37	3.0	1.4	67%	12%	7.4
Edwin Thomas	127	9	25	2.9	2.2	58%	18%	9.8
Alexander Van Oudenaarden	4	0	1		1.0		100%	1.0
John B Vander Sande	14	1	5	1.0	0.6	100%	33%	2.8
Daniel Wang	122	4	11	2.3	1.0	44%	9%	3.9
Shuguang Zhang	23	2	4	1.0	1.0	50%	50%	2.1
Average	**93**	**3.6**	**17.8**	**1.9**	**1.3**	**0.6**	**0.4**	**4.8**
Standard Deviation	**106**	**4.2**	**23.9**	**1.3**	**0.5**	**0.3**	**0.3**	**3.7**

APPENDIX 1 – B: Research Networks Study - Summary Du Pont PI Sample Data

Du Pont PI	Total # of publications	# of academic collaborators	Average # of publ'ns per univ lab	Conc with lead univ	# of publications/yr	Quality
Gregory S. Blackman	2	0			1.0	3
Matthew S. Bogdanffy	42	6	0.8	40%	2.8	36
William E. Farneth	59	15	2.2	36%	3.7	196
David Hallahan	2	2	1.0	100%	2.0	16
Anand Jagota	26	6	2.2	31%	2.0	27
Steve Lustig	11	2	2.0	75%	1.1	31
Vasantha Nagarajan	14	1	1.0	100%	1.0	27
Mark Nelson	22	14	0.7	30%	1.3	114
Bruce Smart	64	2	7.5	93%	2.1	62
Ralph H. Staley	19	7	1.3	22%	2.4	64
Patricia Watson	11	5	1.0	20%	0.5	152
Average	**25**	**5.5**	**2.0**	**0.5**	**1.8**	**66**
Standard Deviation	**21**	**5.0**	**2.0**	**0.3**	**0.9**	**62**

APPENDIX 2 – A: Commercial Outcomes Study – Sample Companies

Company name	Start date	University affiliation
ActivBiotics	1996	Vanderbilt School of medicine, Univ of Washington
Aderis Pharmaceuticals	1994	
Advanced Inhalation Research	1997	MIT, Penn State
Afferent Corporation	2000	Boston University
Agencourt Bioscience	2000	MIT
Akceli, Inc.	2001	MIT
Alantos Pharmaceuticals, Inc.	1999	University Louis Pasteur, College de France
Alnylam Pharmaceuticals	2002	MIT
AltaRex Corporation	1995	University of Alberta
Ancora Pharmaceuticals	2002	MIT
AngstroMedica	2001	MIT
Antigen Express Inc.	1995	U Mass Medical
Aptanomics	2001	Harvard Medical School
Archemix Corporation	2001	Yale, U Texas
AVANT Immunotherapeutics, Inc.	1998	Harvard Medical School
Avocet Polymer Technologies	1996	MIT, University of Chicago
Back Bay Scientific	2000	MIT
Beyond Genomics, Inc.	2000	
Bionaut Pharmaceuticals	2000	
Biopolymer Engineering	1997	MIT
BioProcessors Corporation	2000	
Biostream	1997	Harvard Medical School
BioTrove, Inc.	1997	MIT
CardioFocus, Inc.	1997	
Cellicon Biotech	2000	Boston University
CeNeS Pharmaceuticals Inc	1995	
Centagenetix	2001	MIT
Cetek Corporation	1996	Northeastern University
Coley Pharmaceutical Group	1997	
Collagenesis, Inc	1996	
Collgard Biopharmaceuticals Inc.	1996	
CombinatoRx, Inc	2000	MIT, Harvard
Concurrent Pharmaceuticals	2001	MIT, Harvard
Critical Therapeutics, Inc.	2001	North Shore-Long Island Jewish Research Institute
Curis, Inc.	2000	MIT
Cyclis Pharmaceuticals, Inc.	2001	Harvard Medical School
CytoLogix Corporation	1996	Boston University

APPENDIX 2 – A: Commercial Outcomes Study – Sample Cos (cont'd)

Company name	Start date	University affiliation
Cytomatrix	1995	Harvard Medical School
deCODE	1996	Harvard Medical School
Descartes Therapeutics, Inc.	2002	Harvard Medical School
Domantis, Ltd.	2000	
Dyax Corporation	1995	
Eligix Inc.	1997	
ENANTA Pharmaceuticals, Inc.	1998	Harvard
EndoVia	1996	MIT, Boston University
engeneOS, Inc.	2000	MIT
eNOS Pharmaceuticals, Inc.	1998	MIT
Exact Sciences Corporation	1995	
Fluidigm	1999	
Genitrix, LLC	1998	MIT
GenoMEMS, Inc.	2000	MIT
GenPath Pharmaceuticals, Inc.	2001	Harvard Medical School
Hydra Biosciences	2001	Harvard Medical School
Hypnion, Inc.	2000	Stanford
Idenix Pharmaceuticals, Inc.	1998	University of Alabama, Birmingham
Iguazu Biosciences	2001	MIT, UCSF
InfiMed Therapeutics, Inc.	1998	
Infinity Pharmaceuticals, Inc.	2001	Harvard
Inotek Pharmaceuticals	1996	
KINETIX Pharmaceuticals Inc	1997	
Lightlab Imaging	1998	MIT, Harvard
Living Microsystems	2001	MIT, Harvard Medical School
MDS Proteomics	1999	
Merrimack Pharmaceuticals, Inc.	2000	MIT, Harvard
Microbia, Inc.	1998	MIT
Microbiotix, Inc.	1998	U Mass Medical
MicroCHIPS, Inc.	2000	MIT
Mnemoscience	1999	MIT
Modular Genetics, Inc.	2000	Harvard, Boston University
Momenta Pharmaceuticals, Inc.	2001	MIT
Morewood Molecular Sciences	2001	University of Pennsylvannia
Nano--C	2001	MIT
nanopharma	2001	Harvard Medical School
Nanosys, Inc.	2001	MIT, Harvard, UC Berkeley
Nantero, Inc.	2001	

APPENDIX 2 – A: Commercial Outcomes Study – Sample Cos (cont'd)

Company name	Start date	University affiliation
NEUROMetrix	1996	Harvard Medical School
Novasterilis	2000	MIT
Orasomal Technologies	1996	MIT
Pangaea Pharmaceuticals	1996	Harvard
Parallel Solutions	2001	MIT
Paratek Pharmaceuticals, Inc.	1996	Tufts School of Medicine
Peoples Genetics	2000	MIT, Northeastern
Peptimmune, Inc.	1995	MIT, Harvard
Pharmadyne, Inc.	1996	Boston University
Phylos, Inc.	1997	Harvard Medical School
Pintex Pharmaceuticals	1999	Harvard Medical School
Point Therapeutics	1996	Tufts School of Medicine
PolyGenyx, Inc	1998	MIT
Prana Biotechnology	1997	Harvard Medical School, University of Melbourne
Pro-Pharmaceuticals, Inc.	2000	
Protein Forest, Inc.	2002	
Proteome Systems	1999	
Quantum Dot Corp	1998	MIT, University of Melbourne
Repair	2000	MIT
Rib-X Pharmaceutical, Inc.	2000	Yale
Sangamo BioSciences	1995	MIT
Scion Pharmaceuticals, Inc.	2001	Boston University
Sedecim Therapeutics	2000	Boston University
Sionex Corporation	2001	
Sontra Medical Corp	1996	MIT
Spherics, Inc.	1997	MIT
StressGen Biotechnologies Corporation	2000	MIT
Surface Logix, Inc.	1995	MIT, Harvard
Syntonix Pharmaceuticals, Inc.	1999	Harvard Medical School
Tepha, Inc	1998	
TolerRx Inc.	2000	University of Oxford
TransForm Pharmaceuticals, Inc.	1999	MIT
VisEn Medical	2000	Harvard Medical School
Xanthus Life Sciences, Inc.	2001	MIT, McGill University
Xerion Pharmaceuticals, Inc.	1998	Tufts School of Medicine
Zelos Therapeutics	2001	

APPENDIX 2 – B: Commercial Outcomes Study – Summary Statistics

Correlation matrix

	Idea Quality	Mgmt sum	Mgmt avg	BOD sum	BOD avg	SAB sum	SAB avg	VC sum	VC avg	Invent'r sum
Idea Quality	1.00	0.30	0.22	0.29	0.20	0.23	0.16	0.12	0.08	0.28
Mgmt sum		1.00	0.93	0.52	0.42	0.31	0.08	0.42	0.41	0.11
Mgmt avg			1.00	0.49	0.46	0.29	0.09	0.34	0.43	0.11
BOD sum				1.00	0.79	0.40	0.41	0.43	0.46	0.27
BOD avg					1.00	0.18	0.24	0.22	0.38	0.14
SAB sum						1.00	0.53	0.32	0.33	0.58
SAB avg							1.00	0.01	0.16	0.56
VC sum								1.00	0.47	0.12
VC avg									1.00	0.28
Inventor sum										1.00

REFERENCES

Audretsch, David B., Stephan, Paula E (1996). "Company-Scientist Locational Links: The Case of Biotechnology", *The American Economic Review*, **86(3)**, pp. 641-652.

Baum, J., Calabrese, T. and B. Silverman (2000). "Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology," *Strategic Management Journal,* **21**, pp. 267-294.

Beaver, D (2001). "Reflections on Scientific Collaboration (and its study): Past, Present, and Future. Feature Report", *Scientometrics,* **52(3),** pp. 365-377.

Brookings Institution Report, The (2002). Washington: Brookings Institution Press

Burt, Ronald S. (1992). Structural Holes: The Social Structure of Competition. Cambridge: Harvard University Press

Carter, R.B., Manaster, S. (1990). "Initial public offerings and underwriter reputation", *Journal of Finance*, **45,** pp. 1045–1067.

Goffman, W., Warren, K.S. (1980). Scientific Information Systems and the Principle of Selectivity. Praeger, New York.

Granovetter, M. (1973). "The Strength of Weak Ties." *American Journal of Sociology*, **78(6)**, pp. 1360-1380.

Hansen, Morten T. (1999) "The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits." *Administrative Science Quarterly*, **44(1),** pp. 82-111.

Henderson, R and I. Cockburn (1994). "Measuring Competence? Exploring firm effects in pharmaceutical research" *Strategic Management Journal*, **15**, pp. 53-84.

Henderson, R and I. Cockburn (1996). "Scale, Scope and spillovers: the determinants of research productivity in drug discovery," *Rand Journal of Economics*, **27(1)**, pp. 32-59.

Higgins, H.C., and Gulati, R. (2003). "Getting off to a Good Start: The Effects of Upper Echelon Affiliations on Underwriter Prestige", *Organization Science*, **14(3)**, pp. 244-263.

Huff, A. (1990). Mapping Strategic Thought. Chichester, UK: John Wiley.

Lawrence, P. R. and J. W. Lorsch (1967). *Organization and Environment.* Cambridge, MA: Harvard Graduate School of Business Administration.

Meadows, A.J. (1974). Communication in Science. Butterworths, London.

Mowery D.C, et al (1993), "The growth of patenting and licensing by US universities: an assessment of the impact of the Bayh-Dole Act of 1980" Research Policy

Powell, W. (1990). "Neither market nor hierarchy: Network forms of organisation," in *Research in Organizational Behavior.* Greenwich: JAI Press.

Powell, W, K.W. Kopur, L. Smith-Doerr (1996). "Interorganizational Collabortion and the Locus of Innovation: Networks of Learning in Biotechnology", *Administrative Science Quarterly*, **41(1),** pp. 115-145

Reinganum, J. (1983). "Uncertain Innovation and the Persistence of Monopoly", *The American Economic Review*, **73(4)**, pp. 741-748.

Shane, S, Stuart, T (2002). "Organizational Endowments and the Performance of University Start-ups", *Management Science*, **48(1)**, pp. 154-170.

Stuart, T., H. Hoang and R. Hybels (1999). "Interorganizational endorsements and the performance of entrepreneurial ventures," *Administrative Science Quarterly,* **44**, pp. 315-349.

Utterback, James M (1971). "The Process of Technological Innovation within the Firm", *The Academy of Management Journal*, **14(1)**, pp. 75-88.

Zucker, L. and M. Darby (1996). "Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry," *Proceedings of the National Academy of Sciences*, **93**, pp.12709 - 12717.

Zucker, L, M. Darby and M. Brewer (1998). "Intellectual Human Capital and the Birth of US Biotechnology Enterprises", *The American Economic Review*, **88(1)**, pp.290-306.

Zuckerman, H (1967). " Nobel Laureates in Science: Patterns of Productivity, Collaborations and Authorship", *American Sociological Review*, **32(3)**, pp. 391-403