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STAKES AND STARS: THE EFFECT OF INTELLECTUAL HUMAN CAPITAL ON THE LEVEL AND VARIABILITY OF HIGH-TECH FIRMS' MARKET VALUES

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ABSTRACT

High-tech firms are built much more on the intellectual capital of key personnel than on physical assets, and firms built around the best scientists are most likely to be successful in commercializing breakthrough technologies. As a result, such firms are expected to have higher market values than similar firms less well endowed. In this paper we develop and implement an option-pricing based technique for valuing these and similar intangible assets by examining the effect of ties to star scientists on the market value of new biotech firms. Since firms with more star ties are likely to have a greater probability per unit time of making a commercially valurable R&D breakthrough, we argue and confirm empirically that both the value of the firm and the likelihood of jumps in the value are increasing in the number of star ties. These effects can be financially as well as statistically significant: for two firms with mean values for other variables, the predicted increase in market value of a firm with one article written by a star as or with a firm employee is 7.3% or 16 million 1984 dollars compared to a firm with no articles.

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1 Introduction

High-technology industries are frequently formed or transformed as a result of scientific breakthroughs which open new technological opportunities. During the nascent stage of these scientific/technological revolutions, the top scientists making the key discoveries have a major strategic advantage in exploiting their commercial applications, particularly where need for tacit knowledge of the new techniques creates natural excludability of scientists who have not worked at the bench level with the scientists or are incapable of reverse-engineering their methods from the published articles. Zucker, Darby, and their associates have demonstrated the key role of star scientists who act as scientist-entrepreneurs in determining the time and place of entry and the success of firms exploiting the biotechnology revolution.[1] For example, in this paper we develop and implement an option-pricing based techniques for valuing the intellectual human capital implicit in star ties to firms – and similar intangible assets – by examining the effect of ties to star scientists on the market value of new biotech firms.[2]

Biotech companies with more ties to star scientists have significantly more products in development and on the market and great employment growth than do those with fewer or none.[3] Empirically, the depth of star scientist involvement in the firm is measured by the number of genetic-sequence-discovery articles authored by each of the star scientists as or with employees of the firm.

A natural extension of the Zucker-Darby findings is the hypothesis that high-tech firms with deep star scientist ties should be more highly valued by investors. The size of investors stakes in the risky business of investing in high-tech firms should be determined by their stars. Specifically, the question we address is: What is the effect on high-tech firms' stock market performance of its technology state?[4] In this paper, we argue that there indeed exists such a relationship. In high-tech industries, information about many new discoveries is sufficiently costly to transfer due either to its complexity or tacitness that others are effectively excluded. At the extreme, scientists wishing to build on the new knowledge must first acquire hands-on experience. If scientists cannot gain access to a research team or laboratory setting with that know-how, then working in the new area may be very difficult if not impossible. Thus, we expect the following: the firms with more intellectual human capital are more likely to make technological breakthroughs. Since the technological know-how based on those technological innovations will not be easily grasped by other firms, the firms with this technological know-how should enjoy higher rate of return. This type of higher than normal rate of return will not be competed away until other firms are able to come up with similar or more advanced technology. In the stock market, the shareholders or the firm's potential investors also appreciate the firm's ever-increasing technological state. This eventually will be reflected in the firm's stock price, and correspondingly, in the firm's market valuation.

Average investors may not be sophisticated enough to tell when the firm is having technological breakthrough and how big its effects will be. But ex ante, before they make their investment decisions, they can observe the indicators on the firm's intellectual human capital that may contain useful information about the firm's current technology status and potential future development. For example, they can count the number of scientists in the firm, figure out how many of them have Ph.D. degrees, consider where they did their graduate work, and take into account the size of the firm's R&D expenditure. They can even measure the quality of firm's research team by counting how many big names the firm has or how frequently the firm's scientist are cooperating with academic gurus. This type of ex ante recognition of the firm's potential to make technological breakthroughs will be reflected in the investors' decision making process and consequently be reflected in the firm's stock market price. This makes it possible for us to use stock market information to study the influence of intellectual human capital on the firm's overall success. This also provides a way to value the firm's valuable technological know-how: we can calculate how much of the firm's market value could be explained by certain type of intangible asset, and then value this type of intangible asset based on its contribution to the firm's overall market value. This approach, therefore, could be applied to value such intangible assets as patent citations, scientific citations, ties to star scientists, great ideas.[5]

As argued in Hall (1999), using financial market information to measure the returns of innovative activities has the following advantages: (1) it avoids the problems of timing of costs and revenues (confusion in determining when innovative investments occur and when they generate income stream.) and is capable of forward-looking evaluation; (2) this method is also potentially useful for calibrating various innovation measures, in the sense that one can measure their economic impact using the widely available United States firm data, possibly enabling one to validate these measures for use elsewhere as proxies for innovation value. Following the same spirit, our paper propose a structural model to describe the relationship between the firm's market valuation and its corresponding knowledge assets (i.e. R&D expenditures, "Star Scientist" ties).

Since we argue that the technological innovation affects the investors' valuation. we expect that a certain type of discontinuity in the firm's market value will occur whenever the firm makes frontier discoveries. We propose a endogenous jump–diffusion model in our paper to capture the "jump" nature of technological breakthrough. More specifically, we assume the firm's valued assets (the weighted sum of its intangible assets and tangibles assets) follow a jump-diffusion process with jump intensity endogenously related to the firm's intellectual human capital measure. Thus, whenever the firm makes technological innovation, this breakthrough changes the dynamics of the firm's valued assets. The jump–diffusion process is appropriate here because it not only captures the continuous change of firm's valued assets, but also captures the discontinuity due to extreme events (frontier discovery in our model). In our model, by relating the probability (or frequency) of a jump occurring to a firm's intellectual human capital measures (i.e. number of ties to "star scientist"), we are able to disentangle the effect of intellectual human capital measures on the firm's market valuation. Our theoretical argument is that owning precious intellectual human capital will improve the likelihood of the firm making technological breakthrough. This, in turn, will influence the investors' valuation of the firm's valued assets, which eventually will be reflected in the firm's stock price. By applying a jump–diffusion model, we are able to study this effect in an ex ante manner, which differentiates our approach from the "event study" approach that has been widely used in corporate finance research. This may avoid estimation errors due from identifying "event" and specifying "the windows of event".

The basic framework of this paper is an option-pricing model with underlying asset (valued assets in our paper) following a jump-diffusion process. The basic analytical framework of our study is similar to Black and Scholes' (1973). Cox and Ross (1976), Merton (1976) are among the first economists to apply jump process to option pricing models. But in their studies, jump risks are specified to be unsystematic risk and jump intensity is assumed to be exogenously constant. Bates (1996) and Bakshi, Cao and Chen (1997) study the jump-diffusion process in a more complicated environment. They, together with Heston (1993), use the inverse characteristic function method to obtain the closed form solution for the price of a call option. In this paper, we basically use the same method as the one used in Bates (1996) and Bakshi, Cao and Chen (1997). One contribution of our paper is that we assume the jump intensity to be endogenously related to the firm's intellectual human capital measure. This is different from the constant jump intensity assumption made in the models we mentioned above, which makes our modeling more complicated. By applying the inverse characteristic function technique, we are able to overcome the complexity brought along with the "endogenized" jump intensity assumption and obtain a closed form solution to the price of the European call option, which is just the firm's market valuation in our model.

We use the sample we construct for the biotech industry to test whether our jump-diffusion option pricing model is correctly specified. We compiled the biotech firms that went public during the 1980–1992 time period.[6] For each of those firms, we carefully calculated the links or affiliations to star scientists. We use those "ties" to star scientists as a measure of the biotech firm's intellectual human capital. We also retrieve the firms' accounting information from COMPUSTAT database. By using actual data from the biotech companies, we find that the jump–diffusion option pricing model fits the actual data very well, which implies that there actually exist discontinuities in the firms' market valuation and this type of discontinuity originates from the firms' technological breakthroughs which are made possible by the firms' intellectual human capital. Robustness analyses also confirm that our model is correctly specified. After we estimate the implicit parameters of the jump–diffusion model, we apply this process to study the effect on the firm's market valuation by the firm's intellectual human capital measure — ties to star scientists. Sensitivity analyses illustrate that the increase in the firms' intellectual human capital will lead to higher market valuation. In a reasonable manner, the effects depend on the size of the firm (in terms of total assets), the R&D stock of the firm, the amount of the firm's debts and their maturities. For a typical biotech firm (a firm that has industry average values for its total asset , R&D stock, debt level and average maturity), the first star scientist will generate almost $ 15.73 million in the firm's market value. The contribution to the firm's market value goes down with the increase in the intellectual human capital measure. This is consistent with the assumption that the jump intensity is concavely related to the firm's intellectual human capital measure.

The rest of the paper proceeds as follows. In section 2, we lay out the model and then derive the solution to the model. We provide a detailed description of the data we used in this study in section 3. Econometric methods and the empirical results are provided in section 4. Section 5 further analyzes the robustness of our model and also contains the results of sensitivity analyses. Section 6 discusses and concludes. Appendix A contains details of the proof and Appendix B contains details about how we construct our data sets.

2 The Theoretical Framework

Exploring the effect of intellectual human capital on the firm's market value, or in other words, using firm market as a measure of innovation returns of the firm's intellectual human capital, relies on the fact that publicly traded corporations are bundles of assets (both tangible and intangible) whose values are determined every day in the financial markets. The typical model of market value hypothesizes that the market value of a firm is a function of the set of assets that it comprises:

$$C = G(a_1, a_2, a_3, ...) \tag{1}$$

where C is the firm's market value, a_1, a_2,... are various assets the firm invests in and G is unknown function that describes how the assets combine to create value. If the firm follows value-maximizing behaviors and the stock market is efficient, then the function G will be the value function. In empirical study, the biggest problem associated with this approach is that the functional form of equation (1) is unknown. It is not easy to compute it in closed form if one assumes a realistic profit- maximizing approach for the firm. Most empirical study on this line of research has to fall back on fairly ad hoc functions, such as linear or Cobb-Douglas (linear in logs).

In this paper, we aim to find a near-structural model, which is able to capture the technological innovation nature of high-tech firms. We think this endeavor is able to overcome the naivete of making ad hoc assumptions about the functional form, G; it is also important to help people precisely measure the returns of innovative activities.

In this section we lay out the basic model and then derive the general pricing equation based on our model.

2.1 The Model

Considering the R&D intensive nature and the importance of intangible assets per se in high-tech industries, we define a high-tech firm's valued asset as follows:

$$V(t) = \alpha A(t) + \beta S(t), \tag{2}$$

where A(t) is the value of the firm's tangible assets at time t and S(t) is the value of the firm's intangible assets (this could be proxied by the firm's discounted cumulative R&D expenditures[7]) at time t. V(t) in the above equation is the value of the firm's valued assets. It captures the total value of the firm's assets that are valued by the firm's shareholders. A recent article shows that the correlation between a firm's share price and its book value of equity has dropped from 0.9 in the 60s to about 0.5 in recent years.[8] This demonstrates that the investors not only value the firm's physical assets, but also value the firm's other forms of assets when they make their investment decisions. we think the V(t) we define above is able to capture this story. Note that in equation (2), α and β can be thought as the shadow prices of the firm's tangible assets and intangible assets, respectively. They capture the weights the investors put on the firm's assets when they value the firm. Bothα and β in equation (2) are structural parameters in our model, so we believe them to be stable over time.

We follow the standard practice and specify from the outset a stochastic structure under a risk-neutral probability measure. The existence of this measure is equivalent to the absence of free lunches, and it allows us to value future risky payoff as if the economy were risk-neutral. We pre-specify that the firm's valued asset, V(t), evolves according to the following process:

$$\frac{dV(t)}{V(t)} = (R(t) - \lambda\mu_J)dt + \sqrt{\sigma}dz(t) + J(t)dq(t), \tag{3}$$

and

$$\ln[1 + J(t)] \sim N(\ln[1 + \mu_J] - \frac{1}{2}\sigma_J^2, \sigma_J^2), \tag{4}$$

where:

R(t) is the time–t instantaneous spot interest rate;

λ is the frequency of jumps per year (jump intensity);

σ is the diffusion component of the firm's return variance (conditional on no jump occurring);

z(t) is a standard Brownian motion;

J(t) is the percentage jump size (conditional on jump occurring) that is lognormally, identically, and independently distributed over time, with unconditional mean μ_J. The standard deviation of $\ln[1 + J(t)]$ is σ_J;

q(t) is a Poisson jump counter with intensity λ, that is, $Prob[dq(t) = 1] = \lambda dt$ and $Prob[dq(t) = 0] = 1 - \lambda dt$. We also assume the probability of more than one jump is $Prob[dq(t) \geq 2] = \circ(dt)$, where a function $f(h)$ is $\circ(h)$ if $\lim_{h \to 0} \frac{f(h)}{h} = 0$;

Note that σ_J also captures the dispersion of jump size.

We further assume

$$\lambda = \lambda_0 + \lambda_1 X, \tag{5}$$

where X is the firm specific intellectual human capital measure. By making this assumption, we relate the probability or frequency of jump occurring to the firm's intellectual human capital measure. As we will explain in Section 3, when we estimate the implicit parameters of the model, we define X to be the square root of the number of ties to star scientists ($X = ties^{\frac{1}{2}}$). This type of concave relationship captures the decreasing effect of the firm's intellectual human capital on the probability of technological innovation.

An intuitive interpretation of above process is the following. Most of the time, the firm's total valued assets evolve smoothly, but jumps occur occasionally. The frequency of a jump occurring is endogenously determined by the firm's intellectual human capital state— X in our model. Thus, the above model is able to capture the "technologically innovative" nature of high-tech industries.

Since we specify our model under risk neutral probability measure, λ in above model is not the actual jump intensity. It is the jump intensity under the risk neutral probability adjustment; similarly, μ_J does not capture the actual jump size either. What it captures is the risk adjusted jump size. It is important to realize that the exogenous valuation framework given above can be derived from a general equilibrium in which all risks are rewarded. Bates (1991, 1996) demonstrate how risk premiums for each factor could be derived from a general equilibrium model.[9]

In our model, the jump risks related to the firm's intellectual human capital have both systematic and unsystematic components. So the risk premium for each risk factor is not zero. We are not specifying them in our model, but they have been implicitly internalized in the stochastic structure. The shortcoming of our approach is that the sign and magnitude of jump intensity or jump size may be counter-intuitive, given that what they capture are intensity and size under risk-neutral probability measure.[10] The advantage of this approach is that we do not need to worry about how risk factors interact with each other; So we can just focus on whether there is a jump occurring and how the jump affects the firm's market value. Given the purpose of our study, the above modeling specifications are appropriate.

As Merton (1974) and many other researchers have pointed out, a firm's equity market value could be regarded as a European call option written on the the firm's valued assets with strike price equal to the firm's outstanding debt level and maturity equal to the maturity of the firm's debt. The idea is as follows. If the value of the firm's valued assets is less than the level of debt, then the firm has to go bankrupt and the shareholders get nothing. Since the shareholders get the difference between the firm's valued assets and the portion that goes to debtsholders. Therefore, the firm's equity market value has all the characteristics of a European call option and we can value the firm's equity market value in a option-pricing framework.

We have:

$$C(t,\tau) = e^{-R\tau}E(max(V(t+\tau) - D(t), 0), \tag{6}$$

where $V(t+\tau)$ is the value of the firm's valued assets at time $t+\tau$,D(t)is the firm's debt level at time t, τ is the maturity of firm's debt, and $C(t,\tau)$ is the price of the European option and it measures the firm's equity market value in our model. Note that in equation (6), E is the expectations operator with respect to the risk-neutral probability measure.

Equation (2), (3), (4), (5), (6) summarize the model we use to calculate the firm's market valuation. In the above model, the firm's market valuation is related to its intellectual human capital state through the jump component that appears in the dynamics of the firm's valued assets. This captures the fact that frontier discoveries in science and technology and subsequent commercialization made possible by the firm-specific intellectual human capital (great scientists, great ideas, etc.) have dramatically changed the high-tech industries.

The model we propose above could be seen as a near-structural model. Even though the functional form of G in equation (1) is still based on some assumptions, we argue that the assumptions we made in above model are appropriate in the R&D intensive and technologically innovative environment we are studying in this paper.

2.2 The Solution to the Model

In this subsection, we provide the solution to the model.

Applying the Generalized Ito's Lemma, we know a European call option written on the firm's valued asset with strike price D and term to expiration τ could be solved through the following Partial Differential Equation (PDE):

$$\begin{aligned} 0 &= (R - \lambda\mu_J - \frac{1}{2}\sigma)\frac{\partial C}{\partial V} + \frac{1}{2}\sigma\frac{\partial^2 C}{\partial V^2} - \frac{\partial C}{\partial \tau} - RC \\ &\quad +\lambda\mathbb{E}[C(t,\tau,V(1+J),X) - C(t,\tau,V,X)], \end{aligned} \tag{7}$$

subject to $C(t,\tau) = max\{V(t+\tau) - D(t), 0\}$.

Note that in equation (7), we assume that the risk–free spot interest rate, R(t), and the volatility of the return of the firm's valued assets, σ, are deterministic. This will reduce the complexity of our model dramatically and will not change the results qualitatively.

By analogy with the Black-Scholes formula, we guess a solution of the form

$$C(t,\tau) = V(t)P_1 - D(t)e^{-R\tau}P_2, \tag{8}$$

where the first term is the present value of the firm's valued assets upon optimal exercise, and the second term is the present value of the strike price payment. Both terms have to satisfy the original PDE (7).

In Appendix A, it is shown that the formula for the price of the European call option is as follows:

$$C(t,\tau) = V(t)\Pi_1(t,\tau,V,X) - D(t)e^{-R\tau}\Pi_2(t,\tau,V,X), \tag{9}$$

where the risk-neutral probabilities, Π_1 and Π_2, are recovered from inverting the respective characteristic functions:[11]

$$\Pi_1(t,V,X,\tau) = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty \mathrm{Re}[\frac{e^{-i\phi\ln[D]}f_1(t,\tau,V,X)}{i\phi}]d\phi, \tag{10}$$

and

$$\Pi_2(t,V,X,\tau) = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty \mathrm{Re}[\frac{e^{-i\phi\ln[D]}f_2(t,\tau,V,X)}{i\phi}]d\phi. \tag{11}$$

From Appendix A, we also know:

$$\begin{aligned} f_1(t,\tau,V,X) &= \exp\{[[\lambda_0(1+\mu_J)[(1+\mu_J)^{i\phi}e^{\frac{i\phi}{2}(i\phi+1)\sigma_J^2} - 1] - \lambda_0\mu_J(i\phi+1) \\ &\quad +Ri\phi + \frac{1}{2}\sigma i\phi(i\phi+1)]\tau + [[\lambda_1(1+\mu_J)[(1+\mu_J)^{i\phi} \\ &\quad e^{\frac{i\phi}{2}(i\phi+1)\sigma_J^2} - 1] - \lambda_1\mu_J(i\phi+1)]\tau X + \ln(V)i\phi\} \end{aligned} \tag{12}$$

and

$$\begin{aligned} f_2(t,\tau,V,X) &= \exp\{[R(i\phi+1) + \lambda_0[(1+\mu_J)^{i\phi}e^{\frac{i\phi}{2}(i\phi-1)\sigma_J^2} - 1 - \mu_J i\phi] \\ &\quad +\frac{1}{2}\sigma i\phi(i\phi-1)]\tau \\ &\quad +\lambda_1[(1+\mu_J)^{i\phi}e^{\frac{i\phi}{2}(i\phi-1)\sigma_J^2} - 1 - \mu_J i\phi]\tau X \\ &\quad +\ln(V)i\phi - R\tau\} \end{aligned} \tag{13}$$

Equations(9)–(13) provide the solution to the European call option. As discussed above, the price of this European call option is the same as the firm's market valuation if we take the firm's equity as a call option written on its valued assets with exercise price equal to its debt level. Therefore, if we can estimate the implicit parameters $(\alpha, \beta, \mu_J, \sigma, \sigma_J^2, \lambda_0, \lambda_1)$ in above equations, then we are able to use this formula to estimate the firm's market value. But first, we use the actual data to estimate the model and to test whether our model is correctly specified.

3 Data

This section contains the details on how we construct the data sets for our empirical study. In this paper, we specifically focus on the biotechnology industry. The reasons are as follows:

- The formation and development of biotechnology industry have been largely determined by endowment of intellectual human capital specific to biotechnology (Zucker, Darby and Brewer (1998), Zucker, Darby and Armstrong (1998)). The biotechnology industry is an excellent study field for economists seeking to understand how intellectual human capital affects high-tech industry formation and each firm within the industry;

- As a relatively new industry, biotech has witnessed very active IPO activities. More than 100 biotech companies have gone public during 1979– 1992. For each public firm, accounting and much other firm-specific data have been archived in public databases such as COMPUSTAT and CRSP. This equips us with a relatively complete sample compared to other high-tech fields, especially, when we study the firm's stock market performance. Figure 1 graphs the biotech firms' birth and IPO activities from 1979 to 1992;[12]

- Numerous empirical studies about the biotech industry have established that knowledge assets, or intellectual human capital is crucial to the firm and the industry. However, no studies have focused on the stock market performance of biotech firms; so our study will be a good complement to previous studies. Moreover, the results obtained from our study can be compared to those from other studies, which may deepen our understanding about the roles played by human capital in biotech industries.

Note that even though we only consider biotech industry in this study, the same approach can be applied to studying other high-tech industries without any difficulty. The method proposed in this paper can be applied to industries with the following features: (1) the firms within this industry have substantial intangible assets which have not been valued appropriately by traditional accounting procedures; (2) the firms are competing with others in an R&D intensive and technologically innovative environment, in which frequent technological innovations based on the firms' intellectual capital investment can generate large "jumps" in the value of the firms' assets.

3.1 Biotechnology Firms

We use for the starting point for our firm data set the 752 firms in Zucker, Darby, and Brewer (1998) analysis of the adaptation of biotechnology.For these firms there are extensive data on their intellectual cpital endowment and other variables. Some of these 752 firms are incumbents in this industry, and for these incumbents in industries to which biotechnology is applied such as drugs and food. For these incumbents biotechnology is often a small part of the total value of the firms. In order to focus on the influence on the firm's stock performance of innovations in biotechnology, we limit our sample to the 511 entrant firms that were born after 1975, the "new biotechnology firms". Moreover, in this study, we only consider the firms that have gone IPO. We are able to identify 156 IPOs during 1979-1992 period, but we can only find records for 129 of these public firms in the COMPUSTAT database. For those 129 firms, we retrieved such data as number of outstanding shares, closing stock price, total assets, physical assets, and debts with different maturities.

3.2 Measures of Intellectual Human Capital

Given the purpose of our study, intellectual human capital is the key explanatory variable. In this paper, we measure a biotech firm's intellectual human capital by counting the number of links or affiliations a firm has to the star scientists. The Data Appendix contains the detailed information about how Zucker, Darby, and Brewer (1998) defined star scientist and why we think this variable is a reasonable measure of the biotech firm's intellectual human capital state.[13]

After they identified the star scientist, they hand-collected the 4,061 articles authored by stars and listed in GenBank and recorded the institutional affiliations of the stars and their co-authors on each of these articles. These co-authors are called collaborators if they are not themselves a star. We then define affiliations as the number of articles authored by star scientists affiliated with the firm and links as the number of articles by non-affiliated star scientists writing with one or more firm affiliated collaborators as defined above. We use ties — the sum of affiliations and links to star scientists as the measure for intellectual human capital specific to biotechnology.

In future work we will explore whether or not other measures, such as the number of patents the firm issues, the number of patent citations, and the firm's scientific citations, could also capture firm specific intellectual human capital.

3.3 Other Variables

In this study, we also use some other variables taken from the data sets Zucker and Darby have constructed for their on-going project on "Intellectual Capital, Technology Transfer, and The Organization of Leading-Edge Industries: Biotechnology". A full description of the data and how they are organized can be found in the Data Appendix. Briefly speaking, a dummy variable RTECH captures whether a firm uses recombinant DNA technology. Based on the U.S. Patent Office biotechnology CD–ROM, we have counts of the number of patents granted to the firm by year they are granted and by the year in which they were applied for. We call them Patentg and Patenta, respectively. Also, in order to control for the effects of technology spillover, we count the number of top-quality universities with bioscience programs in the same region as the firm and name it Qual1. From the Venture Economics database, we are able to obtain how many venture capital rounds the firm has received in certain year, the dollar amount of each injection, the stage of venture capital injection. We use NVC to denote the number of rounds and AVC to denote the dollar amount of venture capital injection in each year. We also have the number of research grants and dollar amount of each grant awarded to the firm under the Small Business Innovation Research (SBIR) Program of the federal government. We use Grants to denote the number of grants the firm obtain in certain year. Table 1 and the Data Appendix contain more information about the data sources and how they are defined. The biotech companies' accounting and financial information are obtain from Standard & Poor's COMPUSTAT data base. The variables used in our study include: the observed market value of the firm (C), the debt level (D), the maturity of the firm's debt (τ),[14] total book value of the assets (A), cumulative R&D expenditures (S),[15] and the age of the firm (Firmage). Data Appendix B details how we define each variable. A full list of the variables used in our empirical study could be found in Table 1.

4 Structural Parameter Estimation and Tests of Hypothesis

In this section, we estimate the structural parameters implicit in our model. Based on that, we test the key hypothesis of this paper: Is the actual data from biotech industry able to provide evidence on the discontinuities in the firms' market valuation which could be attributed to star scientists' innovative activities?

4.1 Econometric Method

In Section 2, we explain the logic of taking the firm's equity market value as a European call option written on the firm's valued assets. We also derived the pricing formula for this call option under risk neutral probability measure. In applying option pricing models to estimate the effects of intellectual human capital on firm's market value, one always encounters the difficulties that the structural parameters are unobservable. In our model, the spot volatility of firm's value assets (conditional on no jump), σ; the jump–related parameters $(\lambda_0, \lambda_1, \mu_J, \sigma_J^2)$, the shadow prices of the firm's tangible assets and intangible assets, (α, β), need to be estimated. In principle, one can use econometric methods such as maximum likelihood method (MLE) or the generalized method of moments (GMM) to obtain the structural parameter estimates. In this paper, we employ GMM by adapting the following steps:

Step 1. First, we treat the firm's market valuation as a European call option written on its valued assets with strike price equal to the debt level. Since the firm normally issues debts with different maturities, we cannot simply sum all of firm's debts and assign a date of maturity to it. Here, we compute the firm's total debt level by calculating the present value of the different types of debts. In other words, we discount the debts that will be mature in the future by using short-run risk-free interest rate. The firm's maturity is calculated as the McCauley Duration of the firm's debts, as we explained in Section 3. Intuitively, it could be understood as the weighted average of the maturities of the firm's different types of debts. We stack the observations. Note that with an average of only 3.9 annual observations per firm, we do not attempt to estimate time-series effects and treat each observation as if an individual firm. We believe that this approach is appropriate because in our study we only address the fundamental factors that influence the firm's market value. The structural parameters in our model are expected to be relatively stable over time. Also, the time-series effects, if there are any, may be controlled for by the instantaneous risk free interest rate, the age of the firm, and other variables that relate to the passage of time.

In our empirical study, we intentionally drop the observations with total assets (in 1984 US dollars) less than $15 million. The main reason is that the intellectual human capital measure used in our study is a more appropriate measure of intellectual human capital for the large firms. We identified the star scientists by counting the articles published up to 1990. Using the article counts to identify the firm's ties to star scientists provides a downward bias for the firms that were born late, because those firms may have been formed by young scientists who have little chance to be star scientist as defined in our paper. Most of the small firms dropped from our sample were born in recent years. Including them in our sample may create noise when estimating the model. In addition, some of those small firms have very abnormal stock market behaviors, which we attribute to the well-documented size effect in the empirical finance literature.[16] One possibility is that small firms have some risks which have not been observed by investors. In our study, since we cannot control those unobservable risk factors, it is acceptable to drop the small firms from our sample. Another rationale of dropping small firms is the availability of information. Larger firms are likely to be tracked by more and better analysts. They are also more likely to be scrutinized in the media.[17] Thus, the value of firm-specific knowledge assets could be incorporated into the firm's fundemental value more efficiently. In this sense, our model is more appropriate for firms with larger size and longer history.

For each of the 343 observations for 90 biotech companies, we calculate the debt level, D, and corresponding maturity τ, and count the number of star scientists ties the firm has. Based on this, we calculate the theoretical market value for the firm's equity by using equations (9)–(13). In other words, we calculate $C_i(t, \tau_i; X_i, D_i, V_i)$. Let C_i^* be the observed market value for observation i, calculated by multiplying the closing stock price by the number of outstanding shares. The difference between C_i^* and $C_i(t, \tau_i; D_i, V_i)$ is a function of the values taken by X_i, A_i, S_i, D_i, τ_i, R(t), and by $\Psi = (\alpha, \beta, \mu_J, \sigma_J^2, \sigma, \lambda_0, \lambda_1)$. For each i, define

$$\epsilon_i[\Psi] = C_i^* - C_i(t, \tau_i; D_i, V_i, X_i), \tag{14}$$

where ϵ_i denotes the absolute estimation error of our model.

Step 2. We use the Generalized Methods of Moment (GMM)[18] to estimate the implicit structural parameters in our model. We assume that our model is correctly specified, thus we have

$$E[\epsilon] = 0. \tag{15}$$

We assume that

$$E[\epsilon\epsilon^{'}] = \Omega, \tag{16}$$

where Ω is unrestricted. Suppose now for each observation, i, we observe a vector of J variables, z_i, such that z_i is uncorrelated with ϵ_i. The assumptions imply a set of orthogonality conditions:

$$E[z_i\epsilon_i] = 0, \tag{17}$$

which constitute the moment conditions in our study. It is straightforward that the sample moments will be

$$m = \frac{1}{n}\sum_i z_i\epsilon_i \tag{18}$$

For our model, we assume that the weighted matrix has the following form:

$$\begin{aligned} W_{GMM} &= \frac{1}{n^2}\sum_i\sum_j z_i z_j^{'} Cov[\epsilon_i\epsilon_j] \\ &= \frac{1}{n^2}\sum_i\sum_j z_i z_j^{'} Cov[(C_i^* - C_i)(C_j^* - C_j)] \end{aligned} \tag{19}$$

The minimum distance estimator will be the Ψ^* that minimizes

$$q = m(\Psi^*)' W^{-1} m(\Psi^*) \tag{20}$$

4.2 Estimation and Results

When implementing above procedures, we assume the set of instrumental variables, z, consists of the following variables:

- firm-specific ties to star scientist, Ties;
- the firm's total assets, A;

- the firm's discounted cumulative R&D expenditures, S;
- the counts of granted patents by their application dates, Patenta;
- dummy variable whether the firm applies recombinant DNA technology, Rtech;
- the number of top biotech related programs in the same region as the firm, QUAL1;
- the number of venture capital rounds the firm receives, NVC;
- the years that the firm has been practicing biotechnology, Firmage;
- the number of research grants from SBIR, Grants;
- the firm's debet level, D;
- constant.

Table 2 contains sample statistics for those variables. If our model is correctly specified, we expect that "Ties" captures the value of the firm's knowledge based assets. In that case, we claim that the regressors we defined above will be orthogonal to the error term. Note that we have 7 unknown parameters needed to be estimated and we have 11 moment conditions. Our objective function (20) is obviously non-linear.

We use the Davidson–Fletcher–Powell (DFP) algorithm to estimate the implicit parameter vector Ψ. There are two reasons that DFP algorithm is attractive in our study: (1). DFP algorithm has very strong convergence ability, which is very important for our parameter estimation; (2). When we do the iteration, we have to update the Hessian Matrix, H. In most algorithms, this means that we need to calculate the second-order derivatives of our objective function (20) with respect to the implicit parameters. It is a very demanding task given the complexity of the objective function we have. Using DFP actually avoids this problem.

We adopt the sequential optimization techniques in our estimation. We start from certain starting values and then use DFP algorithm and GMM to estimate the parameters.

After they converge, we use those estimated values as the starting values and repeat above procedure. We repeat this process until we cannot improve the estimates any more. All programs are written in MATLAB. Normally, it takes 7-18 hours to finish one convergence on a devoted Sun workstation. The final results of the estimates are reported in Table 3.

Panel A of Table 3reports the estimates of the unrestricted model. Obviously, all coefficients are significant. However, let us focus on jump-related parameters: $\lambda_0, \lambda_1, \mu_J, \sigma_J^2$. λ_1 is significant, which implies that the probability of jump occurring is positively related to the firm's intellectual human capital measure. Note that the estimated value of μ_J in our model is negative, which is counter-intuitive in sign. But consider the factor that we start our model from a risk neutral probability framework, so μ_J here doesn't capture the real jump size, it only captures the adjusted jump size which already incorporates the risk premium of jump risk.

We use the method proposed by Newy and West (1987) to test our main hypotheses:

$$H_0 : \lambda_1 = 0, \tag{21}$$

and

$$H_1 : \lambda_0 = \lambda_1 = 0. \tag{22}$$

First, we want to test whether there are discontinuities in biotech companies' market value. In other words, whether our suggested model in Section 2 is correctly specified. Newey and West(1987) devise a counterpart of LR test in GMM framework. By applying the same weighted matrix, W, to both unrestricted model and restricted model, we get the minimum distances defined in (20) for both models. The difference between these two should follow a χ^2 distribution with degree of freedom equal to the number of restrictions imposed if H_1 holds. From Panel C of Table 3, it is easy to see that the difference between those two is 30.9. If H_1 holds, it should follow a χ^2 distribution with degree of freedom equal to 4. Obviously, H_1 should be rejected. This means that discontinuities in biotech companies' market value actually exist.

Then, we try to figure out what cause those jumps. We attribute those jumps in the firm's market valuation to the intellectual human capital specific to biotechnology owned by each firm. The argument is straightforward: with that valuable intellectual human capital, the biotech firm is able to make frontier technological innovations more frequently and then convert those innovations to pecuniary benefits by commercializing them. From the investors' perspective, they always face the possibility that the firm's future cash flows may have a dramatic upward shift due to its intellectual human capital, which will be reflected in their valuation of the firm's assets. This will be embodied in their market behavior. So we argue that a firm's stock market performance should reflect investors' expectation based on the firm's intellectual human capital as well as news about outcomes of the R&D. We use the same method as above to test this hypothesis. As Panel B of Table 3 shows, the difference between the minimum distances for the unrestricted model and restricted model (under hypothesis H_0) is 16.8 . If H_0 holds, this difference should follow a χ^2 distribution with degree of freedom 1. H_0 is rejected, confirming that more intellectual capital increases the frequency of stock price jumps.

A few other interesting results can be obtained from Table 3. From Panel A, note that $\beta = 0.8131$, which means investors value high-tech firm's R&D stock; We also find that $\alpha > \beta$ if we consider jump risk related to firm's intellectual human capital measure. This implies that the investors, when evaluating the firm's value, put a higher weight on the firm's tangible assets. In terms of firm's intangible assets, investors do care about them, but more cautiously. We think the investors care more about the quality of firm intangible assets instead of only considering the quantity. We confirm this argument by interpreting the results from the estimation of the restricted model. Once we assume away intellectual human capital related jump risks, we find that the coefficient for intangible assets , β, increases to 2.74 (from Panel C of Table 3), which exceeds the shadow price of the firm's tangible assets, α. With the explanatory power of star-scientist related jump has shifted into β, which makes intangible assets more important. We argue that different types of intangible assets (i.e. R&D stock, ties to star scientist) play subtly different roles in determining the firm's market value.

As noted in Section 3, R&D stock may be a noisy measure of the firm's intangible assets. Some researchers have used R&D expenditures as the proxy for intangible assets. In Table 4, we use R&D expenditures instead of R&D stock as the proxy for S in our model. The story remains. Now, we notice that β has increased to 1.87. In other words, the shadow price of R&D expenditures has increased to 1.87. This magnitude is consistent with the results from other research.[19]

5 Further Empirical Analysis

5.1 Robustness Analysis of the Model

When applying the option pricing model to value certain assets, we should check whether the model used is correctly specified. In other words, we need to check whether it misprices the asset. Our model captures the innovative nature of high-tech companies, it also captures the subtle role played by the firm's intellectual human capital measure. The empirical results in Section 4 also reject the hypotheses that there are no jumps and no intellectual human capital related jumps in the firm's market valuation.

In this subsection, we study our model's in-sample pricing fit. Specifically, for the model we propose, we estimate its implicit parameters. We then plug those parameters into the model to calculate the firm's model value. By comparing the observed market value and the model market value, we are able to obtain our model's pricing error. In order to allow for differences in size of the firms, we use percentage price error as a more appropriate measure of the model's pricing error. We define the pricing error as " Per", where

$$Per = \frac{observed\ market\ value - model\ value}{observed\ market\ value}. \tag{23}$$

If our model is correctly specified, we should expect that the remaining pricing errors of our model, Per, to be uncorrelated with the main explanatory variables in our model estimation. Panel A of Table 5 provides the results of the correlation analysis. In Panel A, it is easy to see that the firm's observed market value, MKV, are significantly correlated with most of the explanatory variables. Especially, we observe that it is correlated with ties to star scientists, number of patents by application dates, R&D stock, the dummy variable for whether the firm applies rDNA technology, the years the firm has been practicing biotechnology, number of top universities with biotech related programs in the same region as the firm. We have used those variables as the measures of the firm's knowledge assets. However, if our model is correctly specified, then the percentage price errors, Per, should be uncorrelated with the variables we described above. Panel A confirms that the model passes this specification test.

To further understand the structure of remaining pricing errors, we conduct a regression analysis to study the association between the errors and the factors that are either market-condition dependent or firm-specific. Empirical studies of option pricing generally find that the pricing errors are related to the moneyness of the option contract. Here, moneyness is a variable used to measure how deep in or how deep out of the money the option is. In this paper, strike price is the debt level, D. And the underlying asset price is defined as the valued asset, $V = \alpha A + \beta S$. We define $\frac{D}{V}$ as the moneyness in our model. Since most of our observations are deep in the money options, we expect moneyness should explain some of the remaining pricing errors. Also, we have assumed that the structural parameters in our model are stable over time, but in fact they may be affected by overall stock market situations in different years. We create year dummies and expect that they should have some explanatory power. We run this regression below for the entire sample:

$$\begin{aligned} Per_i &= \beta_0 + \beta_1 MONEYNESS_i + \beta_{2-12} YEARDUMMIES \\ &\quad + \beta_{13-20} OTHER\ VARIABLES_i + \epsilon_i, \end{aligned} \tag{24}$$

where OTHER VARIABLES in above regression include the natural logarithm of the firm's total assets, the natural logarithm of the firm's R&D stock, ties to star scientist, patents by application dates, dummy if the firm applies rDNA technology, the years the firm has been doing biotechnology, number of venture capital rounds, and top universities in the same region. Panel B of Table 5 reports the regression results based on the whole sample. Not surprisingly, the pricing errors from our model have some systematic moneyness, and year related components. In contrast, the percentage pricing errors are not significantly related to any of the knowledge assets variables and nor to log(total assets) or log(R&D stock). A natural implication is that our model already captures the explaining power of those variables, so nothing is left in the remaining pricing errors.

For comparison, in Panel B of Table 5, we also include the regression results of using log(market value) as the dependent variable. Based on the analyses reported in Table 5, we think our model is well specified.

5.2 Sensitivity Analysis

Empirical evidence shows that the deviation of the firm's stock price from the book value of its assets has increased in recent years. This change has been attributed to ever-increasing important roles played by the firm's intangible assets, especially technological know-how, in determining the firm's market value. Evidence from biotech industry, semi-conductor industry and other high-tech industries already prove this point. Our empirical study provides convincing evidence that the investors do appreciate the intellectual human capital specific to biotechnology owned by biotech firms. Investors' stakes as measured by market value are significantly higher for firms with more star ties. A natural question is how big is this effect. In answering that, the approach we use in our empirical study is shown to be a new method to value such intangible assets as technology know-how.

Table 6 reports the results from sensitivity analysis for biotech firms with different size. Take a biotech firm that has no star ties but otherwise has the industry average values for all its variables as the example. Concretely, this firm has \$81.56 million in total assets. Its R&D stock is valued at \$34.36 million. The firm's overall debt level is \$10.71 million, and the average maturity of its debts is 1.27 years. Here, we also assume that the annual risk-free interest rate is 6%. Based on above assumptions, we find that this firm's market value derived from our model will be \$200.94 million. Consider the effect of increasing the number of its ties to star scientists, our key intellectual human capital measure. As the firm gains access to star scientists, its estimated market value will be improved dramatically. As shown in Table 6, the first tied article with a star scientist will bring about a 15.73 million 1984 US dollar increase in the firm's market value, which accounts for almost 7.3% of the firm's total market value. This result is very striking given the fact that a lot of factors are actually affecting the firm's market value. We think this magnitude is reasonable considering the increased probability of technological innovation brought by this star scientist. He or she not only is able to bring new research achievements to the firms, but also able to point out promising directions, which other scientists of the firm can follow. Further, there is a significant reputation effect: having some big names on the list of the firm's research team makes it easier for the firm to attract more talented scientists.

As we increase the number of ties, we find that the firm's market value keeps on increasing (as reported in Table 6). We also notice that the marginal increase of the market value brought by links or affiliations to star scientists goes down gradually as the number of star scientist ties increases. Algebraically, this is implied by the concave relationship between jump intensity and intellectual human capital measure we assumed in our model. Figure 2 and figure 3 demonstrate this graphically. In sum, the market value results are consistent with declining marginal product as star ties increase and other factors held constant.

The approach used in our empirical study provides a possible way of pricing star scientists. We can value the importance of a star scientist by considering the contribution they may make to the firm's market value. Traditional accounting procedures fail to capture the "tangible" value of the firm's intangible assets, especially knowledge assets. The methodology employed in our study, however, values a firm's intangible assets by taking into account their contribution to the firm's market value.

Our results have some other interesting implications. Financial economists have made a great deal of efforts to test CAPM. Most empirical evidence runs against CAPM. It has been gradually accepted in academic that firm's systematic risk (β) fails to explain the cross-sectional difference in the firms' stock return (or more generally, stock market performance). The recent literature has tried to use size, industry factors, unrecognized sources of risk, etc. to explain the deviation from CAPM model. Our empirical study demonstrates that in high-tech industries, firm-specific intellectual human capital measures have significant power to explain the firm's stock market performance. For example, in this paper, we find ties to star scientists increases the firm's expected market value. We believe other intellectual human capital measures (such as patents, the citations to the firm's patents by other patents) should also affect the firm's changes in market value. This paper provides some insights for those financial economists who are struggling to figure out the "fundamental values" of the firm's assets. Our future research will focus on these issues, especially whether there exists an intellectual human capital index which reflects investors' valuation of the firm's knowledge assets.

6 SUMMARY AND DISCUSSION

Intellectual human capital measured by star ties has been demonstrated previously as a crucial factor that affects high-tech companies' entry and potential for future success. In this paper, we propose a methodology to study whether those intellectual human capital measures have the same effects on firm's stock market performance. By using the data constructed for the biotechnology industry, we are able to identify discontinuities in biotech companies' market valuation. We attribute these discontinuities to more frequent technological advance due to more firm-specific intellectual human capital. Since investors know how crucial those intellectual capital measures are for the firm's success, they include these intellectual human capital measures in their valuation process. Our empirical study provides very convincing evidence.

The approach we used in this paper can also be generalized to value other types of intangible assets, especially when they have the same sort of "innovative" nature involved. We believe our approach provides a method to value firm's intangible assets, an issue on which traditional accounting theory provides little guidance.

Our empirical results also have implications for a widely argued issue: whether CAPM holds? Our study demonstrates that at least we can identify some firm-specific source which can explain firm's stock market performance. Our paper doesn't tackle this issue directly, but it provides convincing evidence that intellectual human capital measures are able to explain some cross-sectional differences in firms' stock market performance.

In our paper, we are not able to test whether other intellectual human capital measures have the same effect. Also, we only look at evidence obtained from biotechnology industry due to the constraints of the data sets we have. Studying other intellectual human capital measures and applying the same approach to other industries are on our future research agenda. We want to compare how different measures capture investors' notice and whether there exists some industry-specific factors which have the same effects as the effects we discovered with star scientists.

Last, but not least, in our study, we take the firm-specific intellectual human capital measure, ties to star scientist, as exogenously given. This is consistent with the view that they largely measure the quality of the scientist-entrepreneurs who start the firm and determine its technological identity. An alternative model would make star ties endogenously chosen by firms that are trying to maximize the benefits attached to that intellectual human capital. In other words, the firms will also take into account the effects of intellectual human capital on their stock prices when they decide whether they are going to increase their investment in obtaining more advanced technology. Our future work should address this issue.

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Endnotes

1. See, for example, Zucker and Darby (1996, 1998), Zucker, Darby, and Brewer (1998) and Zucker, Darby, and Armstrong (1998).

2. As in Zucker, Darby, and Armstrong (1998), the biotech firms ties to star scientists as indicated by affiliateions listed on their genetic-sequence- discovery publications is used as the measure of the firm's intellectual human capital state. The definition of star scientists is laid out in the Data Appendix.

3. Those stars have been very productive. Even though 327 stars are only 0.75 of one percent of the authors in Genbank(1990), they accounted for 17.3 percent of the published articles, almost 22 times as many articles as the average scientist.

4. As a recent article in the Wall Street Journal (February 21, 1999) argues:

> ... Market to book values are at an all time high. What are we to make of this? Some would say the market is simply irrational. Perhaps it is. Another interpretation is that the book value shown on balance sheets doesn't reflect intangible assets such as human capital, management information systems, software and digital distribution systems that are increasingly important in a knowledge-based economy.

We believe that a high-tech firm's human capital plays an even more important role in explaining the firm's stock price.

5. Our paper is complementary to the strand of literature that use financial market information to value the firm's knowledge assets. See Cockburn and Griliches (1987), Griliches (1981), Hall (1993), Pakes (1985).

6.156 biotech firms went public during this period. However, we were only able to find 129 firms that have records in COMPUSTAT database. Among those 129 firms, we intentionally dropped observations with total assets (in 1984 US dollars) less than $15 million. The reasons will be explained in later section.

7.This, however, is a very noisy measure of the firm's intangible assets. In this paper, we define different variables to capture intangible assets. Also, given that we have a structural model, we are able to explore different roles played by different types of intangible assets in our paper.

8. See " A Viking with A Compass", The Economist, June 6th, 1998.

9. Bates(1991) also shows the relationship between the actual jump components and the risk-adjusted jump components. He convincingly demonstrates that the actual jump probability normally have the same sign as the risk-adjusted jump probability, but the risk-adjusted jump size is always downwardly biased compared to actual jump size.

10.As you will see in Section 4, in our estimates, the jump size, μ_J, takes a negative sign. But as shown in Bates (1991), given our parameter estimates, the jump size will take a negative sign if we assume the investors have a preference with degree of risk aversion greater or equal to 3. This is not an outrageous assumption at all.

11.Bates (1996), Heston (1993), Bakshi, Cao and Chen (1997) use the same approach.

12.Births are plotted 1976–1989 only because we are relying on the Zucker, Darby, and Brewer (1998) data base for births which covers 1976–1989.

13.These variables have been validated in many studies as an appropriate proxy for a biotech firm's intellectual human capital state. See, for example, Zucker, Darby, and Brewer (1998), Zucker, Darby, and Armstrong (1998).

14.It is calculated as the McCauley duration of the firm's debts.

15.When we calculate the firm's cumulative R&D expenditures, we assume that the firm's R&D investment depreciates by 15 percent annually.

16.For details about "size effect", see Fama and French (1992), Berk (1995), Daniel and Titman (1997).

17.A number of small firms appear to have been the short-lived results of fraudulent IPOS.

18.See Hansen (1982), Newey and West (1987)for details about GMM.

19.See Hall (1999) for a survey.

Appendix A: Proof of the Option Pricing Formula in Main Text

The valuation partial differential equation (PDE) in main text can be rewritten as:

$$\begin{aligned} 0 &= (R - \lambda\mu_J - \frac{1}{2}\sigma)\frac{\partial C}{\partial L} + \frac{1}{2}\sigma\frac{\partial^2 C}{\partial L^2} - \frac{\partial C}{\partial \tau} - RC \\ &\quad + \lambda\mathbb{E}[C(t,\tau,L+\ln(1+J),X) - C(t,\tau,L,X)] \end{aligned} \tag{A. 1}$$

where we have applied the transformation $L(t) = \ln V(t)$. Inserting the following conjectured solution

$$C(t,\tau) = V(t)\Pi_1(t,\tau,V,X) - De^{-R\tau}\Pi_2(t,\tau,V,X) \tag{A. 2}$$

into (A.1) produces the PDEs for the risk-neutralized probabilities, Π_j, for $j = 1, 2$:

$$\begin{aligned} 0 &= (R - \lambda\mu_J - \frac{1}{2}\sigma)\frac{\partial \Pi_1}{\partial L} + \frac{1}{2}\sigma\frac{\partial^2 \Pi_1}{\partial L^2} - \frac{\partial \Pi_1}{\partial \tau} - \lambda\mu_J\Pi_1 \\ &\quad + \lambda\mathbb{E}[(1+\ln(1+J))\Pi_1(t,\tau,L+\ln(1+J),X) - \Pi_1(t,\tau,L,X)] \end{aligned} \tag{A. 3}$$

and

$$\begin{aligned} 0 &= (R - \lambda\mu_J - \frac{1}{2}\sigma)\frac{\partial \Pi_2}{\partial L} + \frac{1}{2}\sigma\frac{\partial^2 \Pi_2}{\partial L^2} - \frac{\partial \Pi_2}{\partial \tau} \\ &\quad + \lambda\mathbb{E}[\Pi_2(t,\tau,L+\ln(1+J),X) - \Pi_2(t,\tau,L,X)] \end{aligned} \tag{A. 4}$$

Equations (A.3) and (A.4) are the Fokker-Planck forward equations for probability functions. This implies that Π_1 and Π_2 must indeed be valid probability functions, with values bounded between 0 and 1. These PDEs are separately solved subject to the terminal conditions

$$\Pi_j(t+\tau, 0, L, X) = 1_{L(t+\tau)\geq \ln[D]}, \tag{A. 5}$$

where $j = 1, 2$. The corresponding characteristic functions for π_1 and π_2 will also satisfy similar PDFs:

$$\begin{aligned} 0 &= (R - \lambda\mu_J - \frac{1}{2}\sigma)\frac{\partial f_1}{\partial L} + \frac{1}{2}\sigma\frac{\partial^2 f_1}{\partial L^2} - \frac{\partial f_1}{\partial \tau} - \lambda\mu_J f_1 \\ &\quad + \lambda\mathbb{E}[(1+\ln(1+J))f_1(t,L+\ln(1+J),X,\tau) - f_1(t,L,X,\tau)] \end{aligned} \tag{A. 6}$$

and

$$
\begin{aligned}
0 &= (R - \lambda\mu_J - \frac{1}{2}\sigma)\frac{\partial f_2}{\partial L} + \frac{1}{2}\sigma\frac{\partial^2 f_2}{\partial L^2} - \frac{\partial f_2}{\partial \tau} \\
&\quad + \lambda\mathbb{E}[f_2(t, L + \ln(1+J), X, \tau) - f_2(t, L, X, \tau)]
\end{aligned}
\qquad \text{(A. 7)}
$$

subject to the terminal conditions

$$
f_j(t+\tau, 0, X; \phi) = e^{i\phi L(t+\tau)}. \qquad \text{(A. 8)}
$$

for $j = 1, and 2$. Conjecture that the solutions to the PDEs (A.6) and (A.7) are respectively given by

$$
f_1(t,\tau) = \exp\{u(\tau) + y^*(\tau)X(t) + i\phi\ln[V(t)]\} \qquad \text{(A. 9)}
$$

and

$$
f_2(t,\tau) = \exp\{z(\tau) + y_x(\tau)X(t) + i\phi\ln[V(t)] - R\tau\} \qquad \text{(A. 10)}
$$

with $u(0) = y^*(0) = 0$ and $z(0) = y_x(0) = 0$. By the separation of variable technique, we can solve the PDEs as follows:

$$
\begin{aligned}
f_1(t,\tau) &= \exp\{[[\lambda_0(1+\mu J)[(1+\mu_J)^{i\phi}e^{\frac{i\phi}{2}(i\phi+1)\sigma_J^2} - 1] - \lambda_0\mu_J(i\phi+1) \\
&\quad + Ri\phi + \frac{1}{2}\sigma i\phi(i\phi+1)]\tau + [[\lambda_1(1+\mu_J)[(1+\mu_J)^{i\phi} \\
&\quad e^{\frac{i\phi}{2}(i\phi+1)\sigma_J^2} - 1] - \lambda_1\mu_J(i\phi+1)]\tau X + \ln(V)i\phi\}
\end{aligned}
\qquad \text{(A. 11)}
$$

and

$$
\begin{aligned}
f_2(t,\tau) &= \exp\{[R(i\phi+1) + \lambda_0[(1+\mu_J)^{i\phi}e^{\frac{i\phi}{2}(i\phi-1)\sigma_J^2} - 1 - \mu_J i\phi] \\
&\quad + \frac{1}{2}\sigma i\phi(i\phi-1)]\tau \\
&\quad + \lambda_1[(1+\mu_J)^{i\phi}e^{\frac{i\phi}{2}(i\phi-1)\sigma_J^2} - 1 - \mu_J i\phi]\tau X \\
&\quad + \ln(V)i\phi - R\tau\}
\end{aligned}
\qquad \text{(A. 12)}
$$

Q.E.D.

Appendix B: Data

In this paper, we used the data sets developed for the ongoing project on "Intellectual Capital, Technology Transfer and the Organization of Leading-Edge Industries: The case of Biotechnology."(Lynne G. Zucker, and Michael R. Darby, Principal Investigators). A detailed description of the basic data sets developed for above project is presented in Zucker, Darby and Brewer (1998). All data used in this paper will be archived upon completion of the project in the Data Archives at the UCLA Institute for Social Science Research.

Biotechnology Firms

The starting point for our firm data set covered the industry as of April 1990 and was purchased from NCBC(1991), a private firm which tracks the industry. An intensive effort was also made to supplement the NCBC data with information from *Bioscan* (1989 – 1993) and an industry data set provided by a firm in the industry which was also the ancestor of the Bioscan data set (Cetus Corp. 1988).

Based on above efforts, Zucker, Darby, and Brewer (1998) identified 752 US biotech enterprises, of which 512 are classified as entrants, 150 as incumbents and another 90 could not be classified clearly into either subcategory. In this study, we focus on the 512 entrants. In other words, we only look at the firms that were born after 1975. Since our study is about the effects of intellectual human capital on firms' stock market performance, we thus include in our sample only the companies that had gone IPO during 1976–1992. Thus our sample size is reduced to 156 firms. Among these 156 firms, we can only find 130 firms that have entries in COMPUSTAT database. So the final number of biotech companies in our study is 130.

Intellectual Human Capital Measure

Given the purpose of our study, intellectual human capital is the key explanatory variable.

In this study, we measure a biotech firm's intellectual human capital by counting the number of linkage or affiliations a firm has to the "star scientist". The primary criterion for selections of star scientists was the discovery of more than 40 genetic sequences as reported in Genbank (1990) through April 1990. However, 22 scientists were included based on writing 20 ore more articles each reporting one or more genetic sequence discoveries. Thus, Zucker, Darby and Brewer (1998) identified a set of 327 star scientists. These 327 stars were only 3/4 of one percent of the authors in Genbank(1990) but accounted for 17.3 percent of the published articles, almost 22 times as many articles as the average scientist.

They hand-collected the 4,061 articles authored by stars and listed in Genbank and recorded in institutional affiliation of the stars and their co-authors on each of these articles. These co-authors are called collaborators if they are not themselves a star. They then define affiliations as the number of articles authored by star scientists affiliated with the firm and links as the number of articles by unaffiliated star co-authoring with firm scientists. An article with n stars is counted as a link or affiliation for each star. In this paper, we use the sum of affiliations and links to star scientists ties as the measure for intellectual human capital specific to biotechnology.

OTHER VARIABLES

In this paper, we also use a number of other variables. We obtained the patent data for each biotech firm from the CD-ROM Patent Technology Sets, Capital office of Electronic Information Products and Services, US Patent and Trademark Office. We collected patents, which are classified in the following areas of US patent Classification System: Class 935, all subclasses; and class 435, subclass 172.3.

The firms' accounting information are all obtain from COMPUSTAT database, Based on the information we retrieved from COMPUSTAT, we calculate the variables necessary for our study. The variable list is in Table 1, in which we explain how we construct each variable.

We also use some of the variables that have been used in Zucker, Darby, and Armstrong (1998). We define Rtech as a dummy to capture whether the firm has recombinant DNA technology. Also, we define Qual1 to capture the spillover effects of technology. Considering the important role played by venture capitalists in the formation and development of biotech companies, we also use the information about the firm's venture capital financing. It is retrieved from Venture Economics database.

Table 1: Descriptions of the Variables

Section 3 in the text and the Data Appendix include detailed information about the data sources and how we organize our sample. All nominal variables in this list have been converted into 1984 US dollars by using CPI . When we calculated the firm's total debt level, we also included the debt-like liabilities. This solves the problem that some biotech companies never issue debts. When we calculated R&D stock, we only considered the R&D expenditures since the firm went public (we don't have R&D information before the firm went public). So our calculation biases downwardly the size of the firm's R&D stock. As a remedy to this problem, we also use R&D expenditures in certain year as the proxy for intangible assets. Note also that we choose 15% as the depreciation rate of R&D investment because most researchers think this as a reasonable level (see Jaffe (1986)).

Variables	Descriptions
Ties	ties to star scientists: count of number of articles by star scientists who either are affiliated with the firm or co-authored with scientists affiliated with the firm.
X	firm specific intellectual human capital measure in our study: defined as the square root of ties to capture the concave relationship between the firm's market value and its intellectual human capital measure.
C	observed market value: C = closing price X number of outstanding shares.
D	the debt level: calculated as the discounted cumulative value of the firm's debts where the interest rate on 6-month treasury bill was used as the discount rate.
τ	maturity: calculated as the McCauley duration of the firm's debts.
A	total assets: the book value of the total physical assets the firm owns, taken directly from COMPUSTAT database, item 6.
R&D	firm's R&D expenditures: taken from COMPUSTAT, item 46.
S	R&D stock: the depreciated cumulative value of the firm's R&D expenditures with depreciation rate assumed to be 15%.
Patenta	number of patents by application year.
Rtech	dummy variable : = 1 if the firm applies the recombinant DNA Technology, 0 otherwise.
Firmage	the years that the firm has been practicing biotechnology: defined as year-entry year.
Grants	number of research grants by Small Business Innovation Research (SBIR).
NVC	number of venture capital rounds received by the firm in current year.
AVC	dollar amount of the venture capital injected into the firm in current year
Qual1	number of universities in the same BEA defined functional economic area as the firm which have biotech related programs rated 4.0 or higher in the NRC 1982 survey.
R	short-run instantaneous interest rate: we use the interest rate on 6-month treasury bill.

Table 2

Characteristics of the Sample

The sample consists of 343 observations. According to our data, there are 156 biotech firms going public during 1979-1992. For those 156 firms, only 129 have records in the COMPUSTAT database. After dropping the observations with total assets less than $15 million (in 1984 US dollars). The sample size is 90 firms and 343 observations. Note that all nominal variables in this table are expressed in millions of 1984 US dollars.

Variable	Mean	Std.. Dev.	Minimum	Maximum
Ties to star scientist	0.638	2.816	0	28
Square root of ties (X)	0.247	0.761	0	5.29
Observed market value	254.77	660.62	4.496	7334
Total asset	81.566	130.37	15.01	979.56
R&D stock	34.36	62.4	0.295	623.11
R&D expenditure	12.25	21.25	0	192.55
Number of patents by application dates	0.796	1.811	0	14
Number of patents by grant dates	0.900	1.89	0	13
Top universities in the same BEA	1.82	1.019	0	3
Grants from SBIR	0.096	0.411	0	5
Number of venture capital rounds	0.064	0.31	0	2
Years the firm has been doing biotechnology	7.33	2.98	0	16
Debt level	10.71	24.45	0.13	292.19
Maturity of the debt	1.27	0.415	1	3.68

Number of observations: 343 (90 firms observed for a total of 343 years).

Table 3: Estimation of Implicit Parameters and Tests of Hypotheses

The sample consists of 343 observations for 90 biotech public companies. We use GMM method to estimate the implicit parameters. Panel A contains the results for the unrestricted model. After we figure out the unrestricted estimates, we use them to calculate the weighted matrix, W. In Panel B and Panel C, we use GMM to estimate the minimum distance estimators for the restricted models. Note that the weighted matrix we use in Panel B and Panel C is the unrestricted matrix that is solved out in Panel A. Panel D includes the details of our hypothesis tests. Also note that we use R&D stock as the proxy for the firm's intangible assets.

Panel A: Unrestricted Model

	α	β	σ	λ_0	λ_1	μ_J	σ^2_J
Estimate	2.0134	0.8131	0.1164	0.3014	0.2846	-0.3705	0.0938
Standard Deviation	0.0000	0.0000	0.0003	0.0001	0.0001	0.0002	0.0000

χ^2 statistic = 14.77; degree of freedom = 4.

Panel B: Restricted Model (with λ_1= 0)

	α	β	σ	λ_0	λ_1	μ_J	σ^2_J
Estimate	2.9369	1.4370	0.1152	0.2989		-0.4321	0.1209
Standard Deviation	0.0000	0.0000	0.0017	0.0016		0.0024	0.0000

χ^2 -statistic = 31.62; degree of freedom = 5.

Panel C: Restricted Model (with $\lambda_0 = \lambda_1$= 0)

	α	β	σ	λ_0	λ_1	μ_J	σ^2_J
Estimate	2.3400	2.7400	0.1085				
Standard Deviation	0.0000	0.0000	0.0000				

χ^2 -statistic = 45.69; degree of freedom = 8.

Panel D: Tests of Hypotheses

H_1: $\lambda_0 = \lambda_1 = 0$. By using Newy and West (1987)'s D-test, we know that $\chi^2(4) = 30.92$, which is significant at 1% confidence level and H_1 is rejected. Jumps in the firm's market valuation exist.

H_0: $\lambda_1 = 0$. Similarly, we use the D-test. Here, we have χ^2 (1) = 16.85, which is significant at 1% confidence level, so H_1 is rejected. Jumps in the firm's market value are related to firm's intellectual human capital as measured by ties to star scientists.

Table 4

Estimation of Implicit Parameters Using R&D Expenditures Instead of R&D Stock

One challenge to our study is to find the appropriate proxy for the firm's intangible assets. In Table 3, we use R&D stock as the proxy. R&D stock may be a noisy measure of the firm's intangible assets. Some researchers have used R&D expenditures directly as the measure of intangible assets. In this table, we use R&D expenditure (in 1984 US dollars) to proxy intangible assets, S.

The estimation results are reported below. The shadow price of intangible assets, β, has increased from 0.8 to 1.8. The magnitude of increase is consistent with findings of other researchers.(See Hall (1999) for a survey.)

	α	β	σ	λ_0	λ_1	μ_J	σ^2_J
Estimate	2.0481*	1.8720*	0.1181*	0.3001*	0.1223*	-0.3795*	0.0903*
Standard Deviation	0.0000	0.0000	0.0013	0.0004	0.0000	0.0006	0.0000

χ^2 statistic = 13.03; degree of freedom = 4.

* significant at 1% confidence level.

Table 5 Robustness Analyses of the Model

We first define the estimation error of the model as Per: the difference between the observed market value and model value divided by observed market value. Per measures how well the model fits in the actual data. If our model is correctly specified, we expect Per to be uncorrelated with the main explanatory variables in our empirical study. Panel A of this table provides the correlation coefficients for Per and for market value and the other variables. The P-values are included in the brackets. In Panel B, with Per as the dependent variable, OLS regression shows that the estimation errors of our model are mainly explained by the moneyness of the option (defined as debt level / firm's valued asset) and year dummies. This confirms that our model indeed is correctly specified and is able to capture the effects of intellectual human capital and technological innovations on the firm's market valuation.

Panel A: Correlation Analysis N = 343 (Pearson Correlation Coefficients/P-values)

Variables	Observed Market value	Estimation error (Per)
Ties to star scientist	0.45256 (0.0001)	0.06417 (0.2359)
Debt level	0.88806 (0.0001)	0.06271 (0.2468)
Maturity	0.01122 (0.8360)	-0.01704 (0.7532)
Total assets	0.81585 (0.0001)	0.09658 (0.0740)
R&D stock	0.66666 (0.0001)	0.07550 (0.1627)
Number of patents by application dates	0.14573 (0.0069)	0.01290 (0.8119)
Dummy if the firm applies rDNA technology	0.12671 (0.0189)	-0.01043 (0.8474)
Number of top universities in the same region as the firm	0.13342 (0.0134)	-0.01402 (0.7959)
Number of venture capital rounds	-0.04878 (0.3678)	0.07485 (0.1666)
Number of SBIR grants	-0.05285 (0.3292)	0.02499 (0.6446)
The years the firm has been doing biotechnology	0.30759 (0.0001)	-0.01307 (0.8094)

Panel B: Regression Analysis (absolute t-statistics are in parentheses)

Independent Variables	Dependent variables	
	Log (market value)	Estimation error (Per)
Ties to star scientists	0.04693** (3.17)	0.0217 (0.76)
Number of patents by application dates	-0.01584 (0.67)	0.0061 (0.13)
SBIR grants	-0.31367 (0.38)	-0.1044 (0.06)
Venture capital rounds	0.09234 (0.83)	0.2244 (1.05)
Top universities in the same BEA as the firm	-0.01826 (0.51)	-0.0937 (1.36)
Log (total assets)	0.91328** (17.77)	0.1926 (1.89)
Log (R&D stock)	0.11122** (2.53)	-0.0339 (0.38)
The years the firm has been doing biotechnology	0.00510 (0.38)	0.0008 (0.03)
Dummy if the firm applies rDNA technology	-0.10000 (1.33)	-0.1094 (0.75)
Dummy if year = 1986	-0.01384 (0.11)	-0.0287 (0.12)
Dummy if year = 1989	-0.19923 (1.70)	-0.2600 (1.15)
Dummy if year = 1990	-0.33940** (2.92)	-1.0487** (4.67)
Dummy if year = 1991	0.45514** (4.78)	0.5273** (2.87)
Constant	0.86361** (5.17)	-0.6093 (1.82)
Moneyness (D/(2.0134xA+0.8131xS))		-3.2712** (2.25)
Adjusted R^2	0.72	0.10
F- Statistic	68.59	3.74
Number of observations	343	343

** significant at 5% confidence level.

Table 6

Sensitivity Analysis of the effects of Ties on the Firm's Market Valuation

In this table, we calculate the model values for firms with different sizes. We then calculate how the firm's model value increases with the increase of the firm-specific intellectual human capital measure, ties. We choose the firms which are 25th percentile, 50th percentile, 75th percentile, 90th percentile and also the firm which takes industry mean values for its total asset, R&D stock, debt level and maturity. Here, we assume that the short run risk free interest rate is 6%. Based on our model, the contribution of star scientist to the firm's market value depends on the size of the firm. If the star scientists are tied to larger firms, they would bring more value to the firms. All variables are in millions.

	25%		50%		75%	
number of ties	model value	increase	model value	increase	model value	increase
0	55.55		96.61		203.70	
1	58.85	3.30	102.73	6.12	221.15	17.45
2	60.32	1.47	105.48	2.75	229.16	8.01
3	61.50	1.18	107.67	2.19	235.64	6.48
4	62.52	1.02	109.58	1.91	241.37	5.73
5	63.44	0.92	111.31	1.73	246.56	5.19
6	64.30	0.86	112.91	1.60	251.43	4.87
7	65.10	0.80	114.42	1.51	256.04	4.61
8	65.86	0.76	115.85	1.43	260.45	4.41
9	66.59	0.73	117.23	1.38	264.71	4.26

	90%		mean	
number of ties	model value	increase	model value	increase
0	440.42		200.94	
1	494.38	53.9	216.67	15.73
2	520.05	25.67	223.82	7.15
3	541.23	21.18	229.60	5.78
4	560.15	18.92	234.65	5.05
5	577.67	17.52	239.23	4.58
6	594.23	16.56	243.55	4.32
7	610.09	15.86	247.61	4.06
8	625.41	15.32	251.48	3.87
9	640.32	14.91	255.21	3.73

Figure 1 Entries of Biotech Enterprises vs IPOs of Biotech Firms: 1976--1992

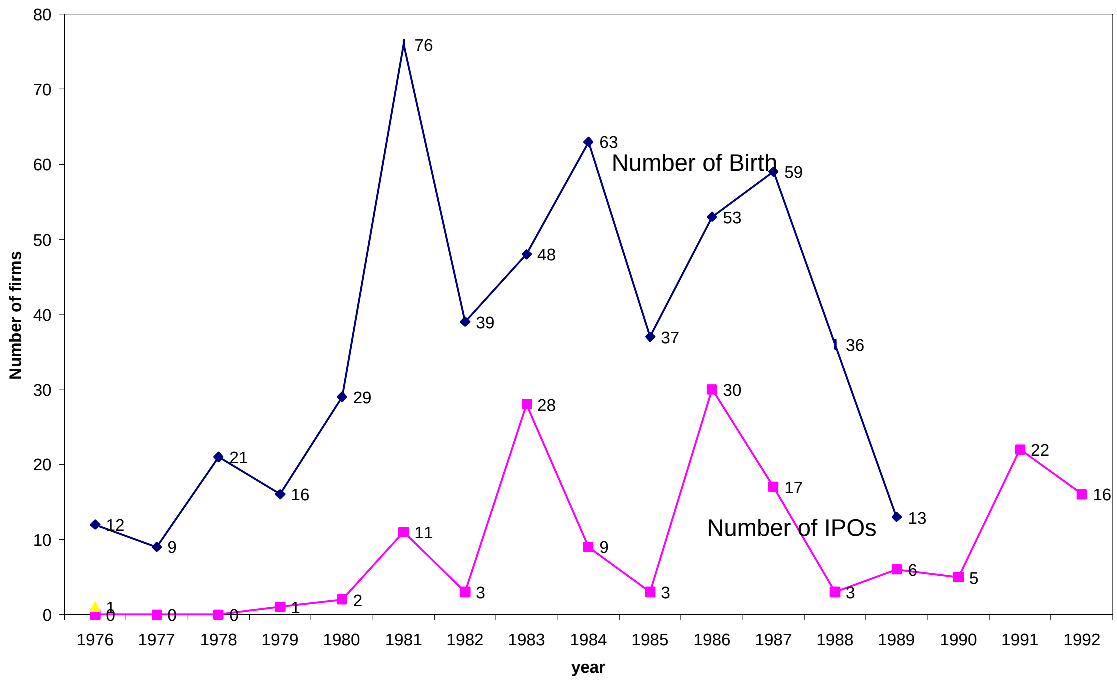

Figure 2: Estimated Effect of Number of Star Ties on a Firm's Market Value

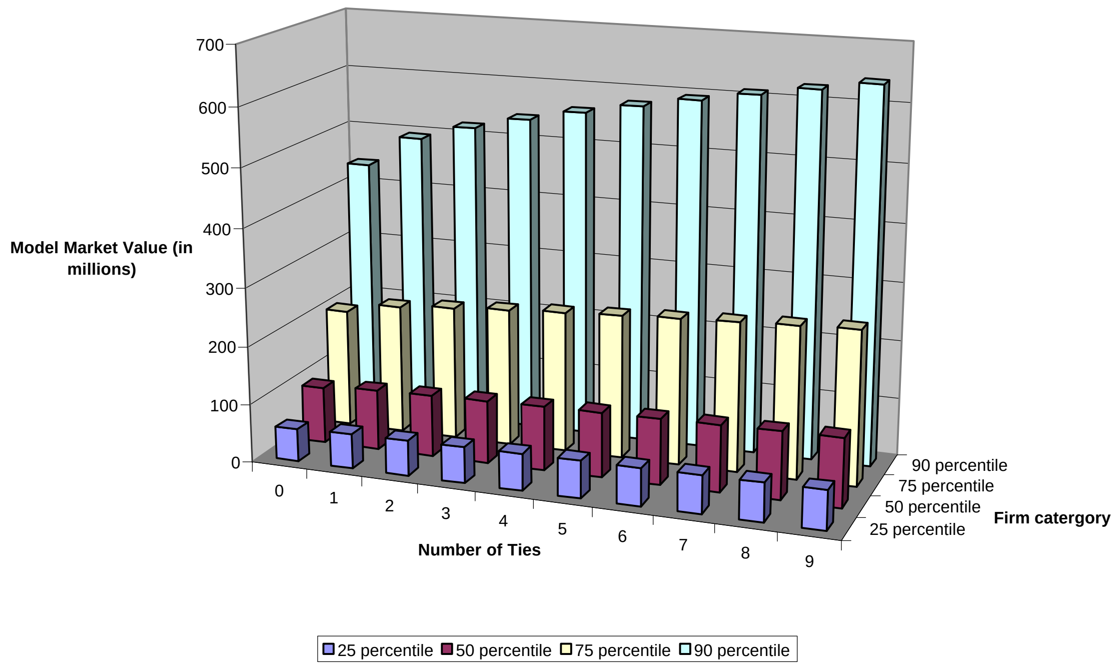

Figure 3:Marginal Increase of Market Value due to Ties as the Number of Ties Increases