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Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology☆

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ABSTRACT

This paper addresses the role that scientific status plays in initial public offerings of technology focused firms. The paper builds on the literature of the sociology of science as well as the work of Spence (1974) and Podolny (1993) and argues that the presence of a Nobel laureate affiliated with a firm making an IPO provides a signal of firm quality to potential investors. Moreover, and building on the work of Podolny and Scott Morton (1999) and Stuart et al. (1999) we hypothesize that the importance of status diminishes as other measures of firm quality become available. We test our hypothesis for two periods of initial public offerings in biotechnology. We document that there is a clear difference in "maturity" of the firms across the two windows on a number of metrics. Consistent with our hypothesis that Nobel laureates play an important role as a non-financial signal of firm quality, we find that first-window firms with a Nobel laureate affiliate realize greater IPO proceeds in the amount of $24 million. In the second window the amount of money raised is not significantly different between Nobel and non-Nobel firms. This finding is consistent with the signaling literature that argues that the importance of a signal is inversely related to the availability of cogent information on firm quality. Consistent with this view, we also find a change between the two windows in the importance of other non-financial metrics used to convey value. Our research is one of the first to examine the dynamic nature of signals. Because we are unable to distinguish the extent to which the reduction in uncertainty at the firm level is correlated with the reduction of uncertainty at the industry level, the question remains as to the extent to which the diminished importance of signals in our second period is due to a change in market uncertainty versus a change in firm uncertainty.

1. Introduction

Merton (1968) may have been the first to call attention to the important role that prestige plays in science but he certainly was not the last. Ever since the articulation of the Matthew Effect, scholars have investigated the role of status, often measured by citations, on numerous outcomes such as pay and promotion. In recent years, this has been extended to examine the role that status plays on the licensing of faculty patents at the institutional level as well as at the individual level. Sine et al. (2003), for example, find that "institutional prestige (as measured by *U.S. News and World Report* graduate school rankings) increases a university's licensing rate over and above the rate that is explained by the university's past licensing performance" (p. 478). At the individual level, Elfenbein (2007) finds the academic output of an inventor to be positively correlated with the likelihood that the inventor's new technologies will be licensed. Elfenbein also finds no evidence that either the payment specified in the contract or the returns of the technology to the university relate to status. He interprets this to mean that "academic status attracts the attention of potential licensees,

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but does not necessarily change their inference about the quality of technologies for sale" (p. 689).

To date no one has examined the role that scientific status has in initial public offerings (IPOs) of technology focused firms at differing stages of an emerging industry's evolution; this paper addresses this question. We build both on the literature of the sociology of science as well as the work of Spence (1974) and Podolny (1993) concerning the role that signals play in markets. Specifically, we argue that the presence of a Nobel laureate affiliated with a firm making an IPO provides a signal of firm quality to potential investors. The status associated with a Nobel laureate not only serves as a signal that implicitly lowers the risk to the buyer (Podolny p. 837) but it also lowers the amount of due diligence required. The status signal is particularly important when there is a high level of overall uncertainty attached to an outcome, as there is in the case of the market for initial public offerings. Moreover, and building on Podolny and Scott Morton (1999) and Stuart et al. (1999), we expect the importance of status to diminish as other measures of firm quality become available.

We test our hypotheses for two periods of initial public offerings in biotechnology by developing an econometric model of the relationship between various metrics of firm quality and the proceeds the firm is able to raise via the IPO. The two windows, which occurred during a period of rapid industrial evolution, correspond to the main biotechnology IPO windows in the 1990s with the first window occurring between 1990 and 1992 and the second window occurring between 1996 and 2000. Our paper is grounded in two observations gleaned from an examination of the IPO prospectuses and S-1 registrations of these firms. First, the prospectuses frequently highlight the research accomplishments of university scientists associated with the firm, some of whom are Nobel laureates. Second, there is a clear difference between the "maturity" of the firms across the two windows. The second-window (1996–2000) firms were typically older, had more granted patents, more alliances and a greater number of products in clinical trials.

Consistent with our hypothesis that Nobel laureates play an important role as a signal of firm quality we find that first-window firms with a Nobel laureate affiliate realize greater IPO proceeds in the amount of $24 million. We also find that the association declines considerably between the two periods; in the second window the amount of money raised is not significantly different between firms with and without affiliated Nobel laureates. We argue that this is consistent with the status signaling hypothesis which makes the point that the importance of a signal is inversely related to the availability of cogent information on firm quality (Podolny and Scott Morton, 1999). Thus, if the presence of a Nobel acts as a status signal, then the greater information available regarding firm quality in the second period should be associated with a decline in the realized gains for firms with affiliated Nobel laureates in the second period. In addition, and also consistent with the work of Podolny and Scott Morton (1999), we find a change between the two windows in the importance of other signals used to convey value. For example, there is less importance attached to the status of the venture capitalists.

This finding of a change in the relative importance of metrics used as signals is important since our research is one of the first to demonstrate the nature of status signals in an emerging industry. We extend existing literature by demonstrating the importance of signals for new entrants in an emergent industry as opposed to new entrants in mature industries (*e.g.*, Podolny and Scott Morton, 1999). Our research also suggests that in nascent markets audiences may initially look to seemingly credible signals inherited from other fields, even those whose accuracy might be quite low. More importantly, while our work is consistent with that of Podolny and Scott Morton (1999), it differs in that we consider entrants into an emerging industry while they consider entrants into an established industry. In their setting status signals facilitate the acceptance over time of new firms by "mature" firms. In our setting status signals, at least initially, facilitate the success of an IPO by new firms in an emerging industry.

What makes this particular market setting both difficult to analyze and important is the fact that the biotechnology market during the 1990s was arguably evolving from one in which there was a great deal of uncertainty regarding the future potential of the industry and uncertainty surrounding the new, nascent firms operating in it. Although "the promise" of biotechnology was never full achieved as the decade of the 1990s progressed (Pisano, 2006), the veil of uncertainty declined leading to more reasonable expectations about the potential contributions of the industry. This initial excitement and maturation process should be expected to influence investors and indeed, as Pisano (2006) notes, investors became more cautious in the latter part of the decade; as a result the threshold for firms to go public increased. This overall transformation coincides with observations about our sample across our two focal periods. These simultaneous reductions in uncertainty were clearly not independent. A question remains therefore, which we are unable to answer with our data, regarding the extent to which the diminished importance of status signals in our second period was due to a change in *market uncertainty* versus a change in *firm uncertainty*.

The plan of this paper is as follows. Section 2 examines the role of signals in markets while Section 3 examines the role and impact university-affiliated star scientists have in biotechnology firms. Accessing the public equity markets for biotechnology firms is discussed in Section 4. Section 5 discusses the data and the sample. We present our regression results in Section 6 and conclude in Section 7.

2. The role of signals

There is a vast literature on the role that signals play in markets. Here we only skim the surface, focusing particularly on the work of Spence (1974) and Podolny (1993).

In a path-breaking 1974 article, Spence developed the theory of market signals in the context of the job market. Spence defines a signal to be an indicator that meets two criteria: (1) it can be altered by the actor and (2) the marginal cost of obtaining the indicator is inversely related to the productive capability of the actor. Thus, for example, a college degree is a signal: it is an indicator that can be manipulated by an individual and the marginal cost of obtaining the signal is less for those having such attributes as "ability" and "organizational skills," characteristics associated with increased productivity. Signals are important in hiring situations because in most job markets the employer does not know how productive the individual will be at the time of the hire. Thus signals can provide useful information to the employer.

Podolny (1993) adapts Spence's model to markets where status is used by customers as a basis for decisions, defining a producer's status "as the perceived quality of that producer's products in relation to the perceived quality of that producer's competitors' products" (p. 830). He argues that, holding quality constant, additional status translates into increased revenue and decreased cost. With regard to the latter, for example, status can provide "free advertising." It can also lower transaction costs, providing "proof" that the product is of a certain quality, or, as the head of a middle-sized investment banking firm told Podolny, when a high status firm such as Solomon or Goldman Sachs calls concerning an underwriting, "we almost don't have to do any diligence; you just say yes" (p. 839). Finally, Podolny notes that status can also lower financial costs either through the firm's ability to obtain capital

or acquire that capital with more favorable terms (Fombrun and Shanley, 1990).[1]

In Podolny's view ties to others can be a particularly effective means for obtaining status. The firm, for example, can obtain status through ties with prominent buyers, ties to other producers or ties to third parties. This view is supported by later work that finds that young companies can acquire status by solidifying relationships with prestigious individuals (Burton et al., 2002). In the biotechnology IPO market ties to other producers or ties to third parties come into play, as we shall see.

Interestingly, the Podolny view of signals, to some extent, stands Spence's view of signals on its head. For in Spence's world, the signal has power because the marginal cost of obtaining the signal is inversely correlated with the attributes that it signals. But in Podolny's world, the presence of status—the signal—lowers the marginal cost of producing a good of a certain quality. It's much like the Matthew Effect: articles of high status authors garner greater attention in part because the cost of seeking "quality" is lower for the reader when the reader restricts her attention to papers authored by high-status scientists.

Podolny (1993) tests his status theory by examining the price charged by an investment bank in underwriting corporate securities. Status is measured by the position of the bank in "Tombstone" ads that announce syndicate members for a given security offering. Syndicate firms are arranged hierarchically into brackets with the higher brackets conferring greater prestige or status. Podolny finds that his measure of status has a significant and negative impact on price, where price is defined as the gross spread divided by the value of the offering.

In later work with Scott Morton (1999), Podolny extends his status model to examine predatory behavior in the case of British shipping cartels from 1879 to 1929. They find that entrants of high social status were significantly less likely to be preyed upon by members of the incumbent cartel than were low status entrants. They also find the strength of this social status effect declines with the entrant firm's age or maturity. From this they infer that the cartel used social status to make inferences regarding how cooperative the entrant owner was likely be. As the firm became older or more mature, and a "visible history of behavior becomes available," the social status signal loses its value (p. 42).

Stuart et al.'s study (1999) of initial public offerings in biotechnology provides additional evidence that the status signal can lose value over time as a firm matures. Status, in this context, is measured by the prominence of affiliates. While the authors find that both the rate of initial public offerings and the market capitalization at the time of the offering is positively and significantly related to the prominence of their strategic alliance partners and investors, they also find that the value of the signal diminishes with the age or maturity of the firm at the time of the offering.

Complementing the Podolny view is a body of theory focusing on imperfect information and the role played by financial intermediaries in evaluating and signaling firm quality to markets (Leland and Pyle, 1977; Campbell and Kracaw, 1980; Chan, 1983; Chemmanur, 1993; Chemmanur and Fulghieri, 1994). Further empirical work explores the roles of venture capitalists (Barry et al., 1990; Meggison and Weisss, 1991), highly ranked underwriters (Beatty and Ritter, 1986; Carter and Manaster, 1990; Carter et al., 1998) and alliance partners (Nicholson et al., 2005). In addition to these external signals, firms may also choose to use internal signals. Ownership retention is one such example; higher quality firms have been shown to retain a higher portion of their shares after IPO (Grinblatt and Hwang, 1989; Brau and Fawcett, 2006).

Finally, it is important to note that status can play a role independent of past performance, although the two are undoubtedly related. To be a bit more specific, and as argued by Sine et al. (2003), past performance provides buyers with a basis for assessing a firm and thus buyers are more willing to engage in transactions with organizations having strong past performance records. But sociological theory also suggests that buyers' perception of the value of an organization's current output is also influenced by an organization's status. The finding by Sine and his coauthors that university prestige increases the licensing rate of university inventions over and above that predicted by past performance provides strong support for the independent role that status can play.

3. The role of university-affiliated star scientists in biotechnology firms

Unlike the extant literature that defines a star based on publication or citation counts (see for example, Rothaermel and Hess, 2007 or Zucker et al., 1998), here we define a star as a university-affiliated scientist who is also the recipient of a Nobel Prize.[2] We choose this criterion because the Nobel Prize is the ultimate scientific accomplishment and there is little ambiguity as to its meaning with respect to the importance of an individual's work. While our definition of "star" might be considered overly strict, the meaning of the prize provides an unambiguous metric by which to explore our research questions. It is a readily available and highly visible sign to the investment community.

Stars—and their university colleagues—make several contributions to knowledge-intensive firms. First, because biotechnology firms are research intensive operations many of their employees are scientists and companies often obtain knowledge through relationships with university-affiliated star scientists. This form of knowledge transfer is particularly important in a field such as biotechnology where knowledge is often of a tacit nature and thus requires face-to-face interaction to effectively transfer knowledge; it is well established that the presence of a star scientist enhances firm performance in biotechnology (Zucker and Darby, 1997; Zucker et al., 2002).[3]

In many instances university-affiliated star scientists play other roles than that of knowledge transfer, serving as reviewers or as links in networks between the firm and universities or the firm and other firms (Audretsch and Stephan, 1996; Powell, 1996). Furthermore, a scientific advisory board (SAB) composed of productive university-affiliated scientists can also play a crucial role in recruiting younger scientists to work with the firm. For example, George B. Rathmann, former Chairman, President and CEO of Amgen, attributed much of the company's success to a SAB of "great credibility" whose "members were willing to share the task of interviewing the early candidates for scientific positions." He went on to say that the young scientists they recruited would not have come to Amgen "without the knowledge that an outstanding scientific advisory board took Amgen seriously" (Burrill, 1988). This is consistent

[1] Drawing on the work of Frank (1985), Podolny also points out that if employees receive intrinsic compensation for working for high status firms, status can also lower the cost of labor.

[2] In our econometric analysis we also consider more traditional measures of star scientists by looking at citation counts to publications of all university-affiliated scientists. We are thus able to parse out the effect between how "star" scientists are defined in the extant empirical literature and how we define it here. There are cases where there are other university-affiliated scientists in a firm that have higher citation counts than the Nobel recipient, but this does not modify the effect of the presence of a Nobel Prize winner.

[3] In a different but related vein, Sine et al. (2003) find that the academic prestige of a university can positively influence the prospect of licensing a university technology. Elfenbein (2007) finds a similar result except that his focus is on the prestige of the university inventor.

Table 1
Examples of Biographical Entries of Nobel Prize Winners from IPO Prospectuses.

R. Bruce Merrifield, Ph.D. (Alteon)
R. Bruce Merrifield, Ph.D., a Nobel Laureate, has been a member of the Scientific Advisory Board since June 1991. He is the John D. Rockefeller Professor of The Rockefeller University. He received his B.A. in Chemistry in 1943 and his Ph.D. in biochemistry in 1949 at the University of California at Los Angeles and joined Rockefeller in 1949. Dr. Merrifield's main scientific contribution, for which he was awarded the Nobel Prize in Chemistry in 1984, was the concept and development of the technique of solid phase peptide synthesis, which is widely used in many areas of biology. He was elected a member of the National Academy of Sciences in 1972. He has received several honorary degrees and awards including the Lasker Award for Basic Medical Research in 1969 and the American Chemical Society Award for Creative Work in Synthetic Organic Chemistry in 1972.

Joshua Lederberg, Ph.D. (Antigenics)
Joshua Lederberg, Ph.D., has been a member of the scientific advisory board since 1996 and is the board's Honorary Chairman. In 1958, at the age of 33, Dr. Lederberg received the Nobel Prize in Physiology of Medicine for his work in the field of bacterial genetics. Dr. Lederberg is currently the Sackler Foundation Scholar and Professor- and President-Emeritus at The Rockefeller University, in New York City, where he is researching the interrelationships of DNA conformation and mutagenesis. Previously, Dr. Lederberg was a professor of genetics at Stanford University. A member of the National Academy of Sciences and a charter member of its Institute of Medicine, Dr. Lederberg has served as chairman of the President's Cancer Panel and has chaired a comprehensive study of emergent infections sponsored by the Institute of Medicine, intended to counteract complacency about the threats from many infectious diseases. He has also received the United States National Medal of Science. Dr. Lederberg has served on the board of the Procter & Gamble Co., and continues as a part-time consultant to several financial and pharmaceutical research and development institutions. He received his Ph.D. from Yale University.

Sir John Vane, D.Sc., F.R.S. (CV Therapeutics)
Sir John Vane, D.Sc., F.R.S., is the Director General of the William Harvey Research Institute at St. Bartholomew's Hospital Medical College in London. Prior to joining that institution, he spent 12 years as group research and development director at the Wellcome Foundation, Ltd. He was awarded the Nobel Prize in 1982 for his work in prostaglandins and for discovering the mode of action of aspirin. Sir John was a research scientist for 18 years at the Royal College of Surgeons of England. He is highly regarded for his continuing research in the areas of cardiovascular disease and chronic inflammation. Sir John holds both a D.Phil. and D.Sc. and is a Fellow of the Royal Society, the Royal College of Physicians and the Royal College of Surgeons.

E. Donnall Thomas, M.D. (Cell Therapeutics)
E. Donnall Thomas, M.D., is the Chairman of cti's Clinical Advisory Board. He is the former Associate Director of Clinical Research and presently a Professor Emeritus at the FHCRC. Dr. Thomas was a founding Member of the FHCRC. His research has spanned a wide array of fields from radiation biology to developmental immunology, and from cancer causing genes to gene transfer therapies. For his pioneering work in BMT, Dr. Thomas was awarded the Nobel Prize for Medicine in 1990. His work demonstrated the feasibility and clinical effectiveness of marrow transplant therapy, and he has contributed to the training of a significant majority of the physicians now performing BMTs worldwide. Among the other honors awarded to Dr. Thomas in recognition of his medical research are the American Cancer Society Award for Distinguished Service in Basic Research and the Kettering Prize of the General Motors Cancer Research Foundation. He is a member of the U.S. National Academy of Sciences.

Baruch S. Blumberg, M.D., Ph.D. (Maygen)
Baruch S. Blumberg, M.D., Ph.D., is a Distinguished Scientist at Fox Chase Cancer Center, Philadelphia, and University Professor of Medicine and Anthropology at the University of Pennsylvania. Dr. Blumberg's research has covered many areas including clinical research, epidemiology, virology, genetics and anthropology. Dr. Blumberg was awarded the Nobel Prize in 1976 for his work on infectious diseases and specifically for the discovery of the hepatitis B virus and has also been elected to the National Inventors Hall of Fame for similar work. Dr. Blumberg's research and insight into infectious diseases are valuable to Maxygen programs related to vaccines and hepatitis B in particular.

with Werth's (1994, p. 22) view that "...most [SABs] are ballast for the letterhead."

The association of high quality university-affiliated scientists can also lend legitimacy to the firm and its quest for resources and is especially important in the absence of tangible assets (Deeds et al., 2004). Indeed, in the early stages of firm development, scientists arguably are a firm's most important asset. This asset is particularly important because biotechnology firms have historically been prematurely born – having limited intellectual property, few, if any, products and hence no internal mechanism for funding research and development (R&D). One way the market can assess the prospects of such firms is by scrutinizing the abilities of the firm's scientists, including those with links to universities. For example, when asked what made DNAX worth $29 million at the time it was acquired by Schering-Plough, a spokesman for the company said, "...the company's assets are far and away the working scientists and the scientific advisory board..." (Kenney, 1986).[4] Such scrutiny may have proved especially effective during the rash of premature births that occurred during the early 1990s in biotechnology.

For these reasons, and because of the asymmetric information between biotechnology firms, venture capitalists, investment banks and the financial markets (discussed more fully in the next section), having a university-affiliated scientist who is a recipient of the Nobel Prize can serve as a very clear metric of quality. Furthermore, it is a metric that might otherwise be missed in a citation count or other measures of quality. Recipients, given the vetting process involved in the selection, can be viewed as the "ultimate stars" in their respective fields. As a result, we argue that investors will view this association with "quality" as a proxy for the underlying research being conducted by the firm. It is not so much that the laureates are doing the firm's research; it is rather that their presence assures investors and the market that the firm's research has been evaluated by the best and that the firm can attract the best in terms of talent. Consistent with this hypothesis, we find that university-affiliated star scientists are highly touted in biotechnology prospectuses. Often these prospectuses read like proposals to the National Institutes of Health, both in terms of the projects that they describe and in terms of the accomplishments of the university-affiliated scientists involved with the firms. Table 1 provides examples of the kinds of entries found in these prospectuses.

4. Accessing capital through the public equity process

For many years the conventional wisdom in biotechnology was that you could only take a firm public if the company had a product in late-stage clinical testing. For example, when Genentech went public in 1980 the company already had an agreement with Eli Lilly to manufacture and market the firm's human insulin product. However, even having a product in clinical trials does not always guarantee a successful offering. The

[4] Scientists are also important assets for mature companies. Robert Swanson, CEO of Genentech, is quoted as saying "Our most important assets walk out in tennis shoes at 5 o'clock." He continues by talking about how these assets tend to walk back in at 10 in the evening to check an experiment, and how full parking lots are at Genentech on the weekend (Burrill, 1988, p. 44).

public equity market is notorious for going through both "hot" and "cold" periods.[5] For biotechnology the equity financing window originally opened in 1980 with the Genentech offering, followed in 1983 by Amgen, Applied Biosystems, Biogen and Chiron. However, by the end of 1984 the equity financing window closed. The window remained closed throughout the rest of the 1980s until early 1990 with activity picking up dramatically in 1991.

In February 1991, Amgen received FDA approval for the first of a new class of genetically engineered drugs designed to boost the immune system's ability to fight infectious disease. This event, along with the success of the Gulf War, ushered in a wave of public funding in biotechnology the magnitude of which had never before been witnessed in the U.S. Within the next 24 months, over 70 biotechnology-related firms went public, raising in excess of $2.3 billion.[6] Perhaps more extraordinary is that many of the therapeutic-focused firms that went public during this period had few, if any products in clinical testing. Sensing an open window during this time, firms rushed to go public. The philosophy was summarized aptly by Joshua Boger, the founder of Vertex, who, speaking retrospectively, said, ". . .the time to go to Wall Street was when Wall Street was ready" (Werth, 1994). This is a phenomenon that is common to the public equity markets in general and not just limited to the biotechnology industry (Loughran and Ritter, 1995).

The central question and concern for an issuing firm in a public equity offering is the amount of money that can be raised, which then directly translates into a measure of firm value. With an established business in a less cutting-edge industry, this is somewhat straightforward, as firm valuations are easier to generate. On the other hand, for biotechnology firms with few or limited products in any stage of clinical testing and the lack of revenues for the foreseeable future, this process is more complex and difficult (Higgins, 2007b). One common valuation method, favored by venture capitalists, attempts to place values on these types of companies using comparables from similar firms (Metrick, 2006; Higgins, 2007b). Unfortunately, accounting data and relevant comparables in many of these cases are simply too unreliable a measure (Ritter and Welch, 2002). Furthermore, finding comparable companies for biotechnology firms is often problematic – sometimes they simply do not exist given the cutting edge nature of the underlying technology. In addition, it is difficult to gauge the market's appetite for a firm whose first substantial earnings prospect are years away, whose flagship product may fail to get regulatory approval, or whose patents may be contested in court.

As a result of these challenges, information asymmetries clearly exist between biotechnology firms that want to raise money and the investment banking community and financial markets. These information asymmetries impact the amount of money biotechnology firms can raise and as a result their underlying valuations. In general, the larger the information asymmetry present, the higher is the risk with which the offering is viewed, and this negatively impacts the amount of money that can be raised (Ritter and Welch, 2002). In an effort to alleviate some of this information asymmetry, non-financial metrics are often used to convey quality. Examples include: prior alliances with pharmaceutical firms (Nicholson et al., 2005), the percent of the firm sold (Brau and Fawcett, 2006), depth of their research pipeline; quality of their patent portfolio (Hsu and Ziedonis, 2007), venture capital backing (Meggison and Weisss, 1991), and the prestige of the underwriter (Meggison and Weisss, 1991; Higgins and Gulati, 2003). The importance of these types of non-financial metrics is supported in recent work by Guo et al. (2005). They argue that non-financial metrics are fundamental to understanding the valuation of biotechnology IPOs, especially given "the frequently negligible earnings, cash flows and tangible assets of most IPOs."

Our earlier discussion provides an additional non-financial metric by which biotechnology firms can convey quality, thereby decreasing the amount of asymmetric information in their offering and as a result increasing the amount of money raised. To wit, the association of highly regarded university-affiliated scientists, namely Nobel laureates, conveys (1) that the firm has able minds working to bring a product to market—if not the minds of the stars themselves, then that of the talent that the stars recruit to work in the firm and (2) that the scientific community itself thinks highly of the firm.

The biotechnology industry provides a fertile setting for a study of firm valuation in a knowledge intensive industry and how the role of signals can evolve over time. First, as noted above, the industry is relatively new. As a result entrepreneurs, investors and the market have had to develop non-financial metrics by which to evaluate firms (and the industry). Second, having two distinct IPO windows allows us to analyze what non-financial metrics firms used to convey or signal value in each period and how these metrics were perceived by the firm's investment bankers and underwriters. What makes these two public equity financing windows particularly interesting is that the early window (1990–1992), in many respects, represented a new biotechnology regime in that (1) these offerings involved firms with little in the way of a market track record, and (2) biotechnology was still a relatively new field with major scientific advances having only recently taken place in the late 1970s. By way of contrast, in the later period (1996–2000) the biotechnology regime was more established in terms of intellectual property, alliances and products in clinical testing, if not more established in sales and the firms making the offerings were more mature. As a result, more information became available to potential investors, the entrepreneurs themselves, and the broader market. The value proposition of the new industry was easier to evaluate. As this "new" industry matured over time, and consistent with the work of Podolny and Scott Morton (1999) and Stuart et al. (1999), we would expect to find changes in the importance of the signals and non-market metrics between the first and second periods. Operationally, this should be reflected in different regression coefficients for signals such as the presence of a Nobel laureate in a model of firm proceeds; specifically, the coefficients on the signal regressors should shrink toward zero. It is impossible to disentangle the degree to which this decrease in signal value is related to a decrease in uncertainty at the firm level versus decreased uncertainty at the industry level.

To summarize, our primary focus in this study is the amount of money a firm is able to raise via an IPO and what drives the underlying determination of firm value (by either the firm's investment bankers or the market). We focus specifically on the non-financial metrics firms utilize in an attempt to differentiate themselves to investors and whether the importance of non-financial metrics changes over time. We see this latter to be of special importance in the context of a developing industry. We are particularly interested in the role that scientific status plays, controlling for other metrics previously shown to be useful. Although we focus on the Nobel Prize ("star scientist"), we also consider reputation by citation counts to articles written by all university-affiliated scientists.

[5] See, for example, Lerner et al. (2003) and Higgins (2007a) for discussions of the difficulty in raising money in cold periods.

[6] Some of the firms included in these counts are only loosely related to biotechnology but took advantage of the window to market themselves as a biotech firm. In our econometric analysis we use a strict filter to identify biotechnology firms solely focused on drug and diagnostic development and excluding such things as agriculture.

5. Econometric model

Data for our sample are drawn primarily from the final IPO prospectuses and S-1 registration filings issued when the firms went public. In establishing our sample we use a narrow definition of biotechnology that includes firms in the following SIC codes: 2834 (pharmaceutical preparations), 2835 (diagnostic substances), 2836 (biological products, except diagnostics), 2869 (organic chemicals), and 8731 (physical research). Firms in these SIC codes are limited to those conducting human drug or diagnostic research. From this we identify 89 firms: 44 for the first period (1990–1992) and 45 for the second period (1996–2000). In using a narrow definition of biotechnology we avoid some issues of unidentified heterogeneity across biotechnology firm "types."

Our definition, and as a result our sample, varies from that of Lerner (1994) and Guo et al. (2005).[7] Lerner's (1994) definition of biotechnology is broad and includes, for example, firms conducting agriculture research. In contrast, Guo et al. (2005) attempt to restrict their sample to ". . .offerings from pharmaceutical and biotech companies (with the three-digit SIC code 283, or the four digit SIC code of 8731)." (p.427). While Guo et al.'s (2005) sample covers the time period 1991–2000 our sample covers the time period 1990–1992 and 1996–2000, which corresponds with the two main biotechnology IPO windows during 1990s. Furthermore, our SIC code coverage is slightly different in that we exclude 2833 (they include) but we include 2869 (they exclude). Finally, we focus solely on biotechnology offerings conducting human or diagnostic research while they consider both pharmaceutical and biotechnology offerings.[8]

We gathered additional deal information from Securities Data Corporation (SDC). Financial and equity information was supplemented from Compustat, Research Insight and CRSP; alliance data was gathered from Deloitte ReCap; patent information was gathered from USPTO; and, product pipeline data was gathered from Pharmaprojects.

5.1. Value – IPO proceeds

The appropriate dependent variable to measure the importance of a Nobel laureate to a biotechnology firm at the time of the IPO is not obvious. Possible choices include: proceeds generated by the IPO (Chemmanur and Fulghieri, 1994; Ritter and Welch, 2002; Zucker et al., 2002), the pre-money valuation of the firm (Stuart et al., 1999), the total value of the firm on the day of the IPO, and that portion of the firm's value that is not sold via the IPO. Here we choose to define our dependent variable, *PROCEEDS*, as the first measure – the amount of money the firm is able to raise (proceeds) via the IPO and we use this variable in our reported analyses (Sections 6.1 and 6.2) below. Our choice is based on the fact that we are dealing with an industry that tends to be cash-constrained, coupled with a long and expensive development process. Thus we are interested in the firm's ability to acquire additional resources. The amount of proceeds raised is determined and set in consultation with the investment bank and can be regarded as an indication of their measure of value of the firm, although clearly it is not a perfect measure.

An advantage of focusing on proceeds is that we avoid issues of overallotment allocations (Aggarwal, 2000; Ritter and Welch, 2002) which could potentially bias a pre-money valuation calculation. Ultimately, however, we demonstrate in our robustness checks that our results are not dependent on the choice of value measure; the econometric results are very similar no matter what measure is chosen and in Section 6.3 we report on the robustness checks using the alternative measures of the dependent variable.

5.2. Nobel laureates

The focus of this paper is the importance of an associated Nobel laureate as a signal of firm quality and stems from the prominence given to star university scientists in IPO prospectuses (see Table 1). We define an indicator variable for whether there is a Nobel Prize winner associated with the firm either as a founder or member of the scientific advisory board (*NOBEL* = 1 if there is an affiliated Nobel Prize winner; 0 otherwise). In the early window, nine of the university-affiliated scientists with eight of the firms had received a Nobel Prize, and in the later window, 10 of the university-affiliated scientists with seven firms had received a Nobel Prize. As argued earlier, star scientists may give credibility to the underlying research being conducted by a biotechnology firm and/or their presence may make it easier for the firm to attract other top scientists. If the presence of a Nobel laureate is a positive signal then *NOBEL* should be positively related to proceeds or firm value.

5.3. Research pipeline and intellectual property portfolio

The future of our sample firms and their potential products is highly uncertain. Not only is there the technical uncertainty involved in development, but also the products must undergo clinical testing and FDA approval. We follow Guo et al. (2005) and include the number of products the firm has in some stage of clinical testing (*PHASE*) as a measure of how far along products are in the development process and how close they are to being submitted for FDA approval.[9] The more drugs or devices in clinical trials, the less uncertain is the future for the firm's product pipeline. *PHASE* is expected to be positively related to firm value. Over the entire sample 53 firms (21 firms in the early window and 32 in the later window) had at least one product in some stage of clinical testing. In the early period the number of products in clinical testing averaged 1.14. In the later period the mean had increased by almost two-thirds to 1.89. The mean of the two counts is significantly different (p-value = 0.047).

In addition to a firm's current research pipeline we also include information about the underlying patent portfolio of each firm. First, we consider the number of patents to which the firm has exclusive rights at the date of their public equity offering (*PATENTS*).[10] Thirty-five firms (6 in the early window and 29 in the later window) have patents by the date of their public equity offering. For firms with patents the mean number of patents in the early period is 3.6 and in the later period it is 10.5. The average number of patents per firm is 0.5 in the first period and 6.7 in the second (p-value for the difference is 0.003). Second, as a measure of how important (fundamental) these underlying patents are we also

[7] Guo et al. (2005) identify 343 biotechnology IPOs between 1991 and 2000 while Lerner (1994) identified 68 biotechnology IPOs between 1990 and 1992. While Guo et al. (2005) started with 343 IPOs they exclude 221 from their study for a final sample of 122.

[8] While our definition and sample are slightly different from Guo et al. (2005) there are similarities, which we will discuss, between our results.

[9] Clinical testing is broken down into three phases: Phase I involves safety testing; Phase II focuses on small-scale human efficacy trials; and, Phase III focuses on large-scale human efficacy trials.

[10] The patent variable was coded from the final IPO prospectuses and measures the number of patents to which the firm has exclusive rights. Thus, the measure captures not only patents issued directly to the firm, but patents acquired through arrangements with other firms. In several instances where the prospectuses did not report patent information, the patent variable was constructed by measuring the number of patents (as reported by the U.S. Patent Office) issued to the firm up to the date of the IPO.

include the number of U.S. citations received within 3 years after the date of the public equity offering (*PATENT_CITES*). In the early window, the average number of citations per patent was 1.68. By the later window the average had risen substantially to 20.36. Citations per firm, however, rises from 1.1 to only 2.8 (the difference is not statistically significant). Consistent with prior work (Hall et al., 2005) we expect *PATENTS* and *PATENT_CITES* to be positively related to firm value.

5.4. Strategic alliances

An extensive literature focuses on strategic alliances between biotechnology and pharmaceutical firms. However, the effect these alliances have on the proceeds of public equity offering is uncertain. On the one hand, Nicholson et al. (2005) show that having an initial alliance with a pharmaceutical firm serves as a positive signal to the market.[11] Such an alliance should be viewed as a relationship that will be beneficial to both parties. As a result, a portfolio of many alliances can positively impact the amount of money a firm can raise. On the other hand, alliances can also create an encumbrance on future activities, revenues and/or intellectual property ownership (Guo et al., 2005). These issues can be exacerbated depending on how the underlying control rights are allocated (Higgins, 2007a; Adegbesan and Higgins, 2011). Essentially, it is possible that a few alliances can provide a positive signal about the firm whereas many alliances might be a negative signal due to potential future encumbrances.

Over the entire sample 70 firms had at least one alliance. Only 28 of the 44 firms in the early window had alliances while 42 of the 45 firms in the later window had alliances. The average number for the 44 firms in the early period was 3.6 while the average in the second period was larger at 8.2 alliances; the difference is statistically significant. Maximum numbers of alliances, however, are similar: 32 for one firm in the early window and 35 for a firm in the later window. To capture the potential nonlinear effect of the number of alliances we include both the number of alliances (*ALLIANCES*) and the square of the number of alliances (*ALL_SQ*). Consistent with the above view, our expectation is that *ALLIANCES* will have a positive coefficient and *ALL_SQ* will have a negative coefficient.

5.5. Percent of the firm being sold

The percentage of the firm to be sold during a public equity offering represents an important decision for the owners given the loss of control and future returns that occur as more of the company is sold. While it is doubtful that the market cares a great deal about the loss of control, it is likely that the market would view a sale of a large portion of the firm as a negative sign (Leland and Pyle, 1977; Grinblatt and Hwang, 1989; Brau and Fawcett, 2006). If the current owners seek to divest themselves of a large share of the company, then it may be that they have negative inside information. To capture this effect we include the log of the percent of the total shares of the firm that are sold (*PERCENT_SOLD*). Therefore, we expect *PERCENT_SOLD* to be negatively related to firm value. The percent of the company sold varies from 3.7 to 42.1% with a mean of 11.9% in the early window and 11.7 to 35.9% with a mean of 22.2% in the later window. The means are significantly different (p-value = 0.0).

[11] For the semiconductor industry Hsu and Ziedonis (2007) find that the impact of reputable alliance partners diminishes when patent stocks are taken into consideration.

5.6. Reputation of investment bankers

The effect of the investment bank's reputation on public equity offerings is well studied in the finance literature. Higher quality firms serve to reduce information asymmetries and mitigate the adverse selection problems faced by external investors (McLaughlin et al., 2000). Additionally, firms issuing equity can signal favorable private information by choosing higher quality investment banks (Booth and Smith, 1986; Titman and Trueman, 1986; Carter et al., 1998). Chemmanur and Fulghieri (1994) argue that investors use the past performance of an investment bank to determine credibility. Their findings suggest that higher reputation firms generate higher IPO proceeds. As a result, we follow Meggison and Weisss (1991) and construct a proxy for the reputation of the investment banking firm based upon relative market share. For each year of our sample we rank the top 25 investment banks based upon total IPO proceeds gathered from SDC. Relative market shares for the investment banks are then determined.[12] The means for the two periods are not significantly different. Consistent with Chemmanur and Fulghieri (1994) we expect manager market share (*MGR_SHARE*) to be positively related to firm value.[13]

5.7. Additional firm controls

The majority of our firms have limited product-based revenues. Most of the revenues they do have are from strategic alliances, grants or other types of research funding. As such, determining the size of the firm based on a measure of revenues or total assets would be inappropriate. We follow Graham and Higgins (2010) and use the number of employees (*EMPLOYEES*) to proxy firm size. The biotechnology industry is knowledge intensive and a firm's most important asset may very well be intangible in nature. As a result, all else being equal, larger firms should be able to raise more money than smaller firms. The correlation between revenues and the number of employees is positive but small (0.37). The number of employees ranges from 5 to 276 with a mean of 74.4 over the entire sample. Firms in the early window are smaller (58.8 employees on average) than the firms in the later window (89.6 employees on average). These means are statistically significantly different (p-value = 0.015).

In addition to the prestige of the underwriter we follow the literature (*e.g.*, Meggison and Weisss, 1991; Brau and Fawcett, 2006) and control for venture capital backing for the firm. In the early period 40 of the 44 firms had venture backing while in the later period only 34 of 45 were venture backed. Rather than use an indicator of whether the firm had venture capital backing we follow Higgins and Gulati (2003) and create a measure of the prominence of the venture capitalist. *VCPROM* is created as follows: we generated rankings of venture capitalists from VentureXpert based on total dollars invested by each firm in each of the years that comprise the timeframe for the dataset. Firms are coded as 1 if any of the biotechnology firm's venture capitalists with a minimum of 5% stakes were listed as among the top 30 on the list of prominent venture capitalists for the year prior to the firm's IPO date, and they are coded as zero otherwise.

Market conditions are one of the main factors that influence a firms' decision to go public (Lerner, 1994). As noted earlier, IPO markets go through 'hot' and 'cold' periods. In order to control for

[12] In each year, the 25th ranked underwriter had a relative market share of 0.1%. As a result, we assigned a relative market share of 0.1% to any underwriter that was in the sample that was not on this list of 25.

[13] In addition to the reputation of the investment banker we also considered the breadth of the underwriting syndicate since it is possible that a Nobel affiliation with the firm might garner more attention. It was not significant, however, in any specification.

Table 2
Summary statistics.

Variable	Panel A: early period ($n=44$)			Panel B: late period ($n=45$)			p-Value
	Mean	Min	Max	Mean	Min	Max	
PROCEEDS[a]	41.00	4.80	136.80	64.02	12.80	250.15	0.007
NOBEL	0.18	0.00	1.00	0.16	0.00	1.00	0.744
PERCENT_SOLD	11.91	3.73	42.11	22.19	11.74	35.90	0.000
ALLIANCES	3.59	0.00	32.00	8.18	0.00	35.00	0.008
EMPLOYEES	58.84	5.00	172.00	89.62	8.00	276.00	0.013
MGR_SHARE	0.03	0.00	0.18	0.04	0.00	0.24	0.734
PHASE	1.14	0.00	8.00	1.89	0.00	7.00	0.051
PATENTS	0.50	0.00	9.00	6.64	0.00	70.00	0.004
PATENT_CITES	1.07	0.00	36.00	2.76	0.00	63.00	0.357
R&D_EXPEND[a]	13.17	0.43	52.95	24.63	2.43	117.05	0.002
VCPROM	0.39	0.00	1.00	0.29	0.00	1.00	0.337
BIO_RATIO	0.11	0.06	0.12	0.12	0.03	0.17	0.210
NOBEL_AGE[a]	5.75	1.00	16.00	23.29	5.00	42.00	0.021
REVENUES[b]	5.67	0.00	48.31	12.04	0.00	142.55	0.085
TOTAL_CITES	1.00	0.09	5.00	2.26	0.18	8.96	0.000
MAX_CITES	351.93	34.00	1307.00	678.84	81.00	1921.00	0.000
AGE	51.68	3.00	124.00	71.07	15.00	193.00	0.013
CUM_BIOTECH	22.50	1.00	44.00	67.30	45.00	89.00	0.000

[a] Calculated only for firms with Noble laureates.
[b] Millions of current dollars.

Table 3
Simple correlations.

	PROCEEDS	*NOBEL*	*PERCENT_SOLD*	*ALLIANCES*	*MGR_SHARE*
NOBEL	0.080				
PERCENT_SOLD	0.067	−0.131			
ALLIANCES	0.099	−0.035	0.332		
MGR_SHARE	0.226	−0.013	−0.038	0.091	
R&D_EXPEND	0.352	0.110	0.094	0.266	0.221
EMPLOYEES	0.206	0.109	0.192	0.335	0.252
PHASE	0.174	−0.062	0.243	0.113	−0.201
PATENTS	0.580	−0.118	0.038	0.181	0.028
PATENT_CITES	0.333	−0.090	0.032	0.043	0.039
VCPROM	0.024	0.060	0.075	0.010	0.141
BIO_RATIO	0.503	−0.077	−0.017	0.134	0.288

	R&D_EXPEND	*EMPLOYEES*	*PHASE*	*PATENTS*	*PATENT_CITES*	*VCPROM*
EMPLOYEES	0.367					
PHASE	0.126	−0.125				
PATENTS	0.267	0.051	0.017			
PATENT_CITES	0.105	0.089	0.041	0.264		
VCPROM	0.174	0.151	0.007	0.007	−0.132	
BIO_RATIO	0.352	0.048	0.077	0.233	0.240	−0.027

the market conditions for biotechnology IPOs, we define *BIO_RATIO* as the ratio of biotechnology IPOs divided by the total number of IPOs in a given year. We expect larger values of *BIO_RATIO* to be positively associated with firm value.

Finally, for firms engaged in R&D activities it is common to use the ratio of R&D expenditure to revenue as a measure of R&D "intensity." However, each of these firms is R&D intensive and their revenue streams are generally small. In addition, and perhaps more importantly, the revenue streams are largely from license revenue and revenue stemming from alliances rather than revenue from product sales. For this reason we doubt that the value of current revenue is a valid predictor of the potential success of these firms. As a result, rather than use the ratio of R&D expenditure to revenue we use only the level of R&D expenditures. To smooth out the figures we use the sum of R&D expenditures (measured in current dollars) for the 3 years prior to the public equity offering (*R&D_EXPEND*). Since all of these firms are R&D intensive (indeed, they are not much more than a "bundle" of R&D and intellectual property), what is likely to be the case is that this, along with the number of employees, will be a measure of firm size and therefore should have a positive effect on firm value.

5.8. Summary statistics

Summary statistics for the early and later windows are found in Table 2, Panels A and B, respectively and simple correlations are in Table 3. The summary statistics in Table 2 are separated by IPO window to emphasize the fact that the firms in the second period are more mature and much further along in their development than those in the early period in the sense that the levels of the variables are generally greater in the later window. With the exception of *VCPROM*, *NOBEL* and *BIO_RATIO* all later window levels are greater than early window levels. The last column of Table 3 gives p-values from tests of differences in the average values. With only a few exceptions, the means are statistically significantly different.

The higher values of the regressors in the second period allow for a test of the market signaling presence of Nobel laureates. The signaling literature is clear in suggesting that the value of a signal diminishes in the presence of observed measures of quality. Thus, if the presence of a Nobel laureate is a signal of firm quality, then the value of that signal should be less in the second period than in the first period given the greater values of observed measures of firm quality such as *PHASE*, *R&D_EXPEND*, etc. Below we show that this is precisely the case in our data.

Also, in Table 2 summary statistics are presented for six regressors we consider in our robustness checks. To capture any time depreciation in the value of a Nobel to the success of a firm we include the product of the indicator of the presence of a Nobel laureate and the number of years since receiving the award (*NOBEL_AGE*).[14] The statistics for *NOBEL_AGE* are calculated only for the firms with a Nobel laureate. The mean elapsed years since the awarding of the Nobel for early period firms is 5.75 years which is statistically significantly smaller than the 23.29 years for the later period. We also consider the total of revenues received by the firm in the 3 years prior to the IPO (*REVENUES*), the total number of citations to publications of all the university affiliated scientists (*TOTAL_CITES*), the maximum number of citations received by the university affiliated scientists (*MAX_CITES*), the cumulative number of biotechnology IPOs (*CUM_BIOTECH*) and the age in months of the firm at the time of the IPO (*AGE*). The mean level of each of these variables is statistically significantly larger in the second window.

Finally, we note that none of the firms had a marketable biotechnology product at the time they went public. Several had revenue from strategic alliances and other relationships, but all were operating in the red and sales-based revenue was generally small. For the 3 years prior to their offering, 21 of the early-window firms had revenue of less than $1.3 million, while only 6 had revenue in excess of $13 million (in current dollars). Average total revenue for these firms in the 3 years prior to their offering was $5 million. In contrast, for the 3 years prior to their offering, only 11 of the later-window firms had revenue of less than $1.3 million, while 13 had revenue in excess of $13 million (in current dollars). Average total revenue for these firms in the 3 years prior to their offering was approximately $10 million. It is remarkable that despite having no marketable products and limited revenue, the average amount raised by the IPO (based on proceeds) was $41 million in the early window and $64 million in the later window.

5.9. Early versus later window controls

The substantial difference in the levels of most variables across the two windows suggests the possibility of changes in the levels of coefficients; this is particularly the case if our hypothesis of diminished importance of signals in the second period is correct. To test for the presence of coefficient changes we define the indicator variable *LATE* to be equal to one if the window is the period 1996–2000 and zero otherwise. *LATE* is interacted with each of the above variables:

L_NOBEL	=	*LATE*NOBEL*
L_PERCENT_SOLD	=	*LATE*PERCENT_SOLD*
L_ALLIANCES	=	*LATE*ALLIANCES*
L_ALL_SQ	=	*LATE*ALL_SQ*
L_EMPLOYEES	=	*LATE*EMPLOYEES*
L_MGR_SHARE	=	*LATE*MGR_SHARE*
L_PHASE	=	*LATE*PHASE*
L_PATENTS	=	*LATE*PATENTS*
L_PATENT_CITES	=	*LATE*PATENT_CITES*
L_R&D_EXPEND	=	*LATE*R&D_EXPEND*
L_VCPROM	=	*LATE*VCPROM*
L_BIO_RATIO	=	*LATE*BIO_RATIO*

If the coefficient of an interaction term is not significantly different from zero, then that variable has the same marginal effect in each period. If the coefficient of an interaction term is significantly different from zero, then the second period marginal effect is the sum of the first period coefficient and the coefficient of the interaction term.

[14] In those firms with more than one Nobel Laureate we use the most recent Nobel to calculate *NOBEL_AGE*.

Table 4
PROCEEDS regressions results.

		Coef.	*t*-Stat		Coef.	*t*-Stat	
1	*NOBEL*	0.7137	3.25	***	0.7474	4.15	***
2	*PERCENT_SOLD*	−0.0232	−0.13		0.0156	0.12	
3	*ALLIANCES*	0.0596	1.96	*	0.0510	2.05	**
4	*ALL_SQ*	−0.0032	−2.87	***	−0.0029	−3.56	***
5	*MGR_SHARE*	0.0488	1.12		0.0266	0.91	
6	*R&D_EXPEND*	0.3279	2.22	**	0.2934	2.98	***
7	*EMPLOYEES*	0.0769	0.43		0.1473	1.86	*
8	*PHASE*	0.0781	2.10	**	0.0759	3.02	***
9	*PATENTS*	−0.0550	−0.69		0.0173	5.51	***
10	*PATENT_CITES*	0.0169	0.97		0.0048	1.88	*
11	*VCPROM*	0.3682	2.02	**	0.3685	2.16	**
12	*BIO_RATIO*	2.4204	0.74		−2.7984	−0.91	
13	*LATE*	0.1435	0.09				
14	*L_NOBEL*	−0.7907	−2.29	**	−0.8621	−2.87	***
15	*L_PERCENT_SOLD*	0.0431	0.11				
16	*L_ALLIANCES*	−0.1079	−2.44	**	−0.0915	−2.37	**
17	*L_ALLSQ*	0.0046	3.20	***	0.0041	3.70	***
18	*L_MGR_SHARE*	−0.0407	−0.67				
19	*L_R&D_EXPEND*	−0.2747	−1.39		−0.2045	−1.40	
20	*L_EMPLOYEES*	0.0863	0.42				
21	*L_PHASE*	0.0003	0.01				
22	*L_PATENTS*	0.0735	0.93				
23	*L_PATENT_CITES*	−0.0100	−0.57				
24	*L_VCPROM*	−0.5779	−2.15	**	−0.5805	−2.37	**
25	*L_BIO_RATIO*	4.7351	1.12		10.0305	2.70	***
	Observations	89			89		
	R-Square	0.695			0.682		

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

6. Econometric results

6.1. Main results

The method of estimation is least squares with robust standard errors and the dependent variable, *PROCEEDS*, is the amount of money the firm is able to raise via the IPO. Fixed and random effects were considered using year effects. A Hausman test revealed no significant difference in the estimators. However, the random effects model revealed a zero variance for the cohort effects; thus ordinary least squares are appropriate. All data are converted to logarithms with the exception of the indicator variables *LATE* and *VCPROM* and the count variables *PATENTS*, *PATENT_CITES* and *ALLIANCES*, as well as *ALL_SQ* and *BIO_RATIO*.

Results are in the first panel of Table 4. The first 12 rows 1–12 in Table 4 give the first window coefficients and *t*-statistics (i.e., results when *LATE* = 0). As noted above, the coefficients for the second window are obtained by adding the first period coefficient to the coefficient of the interaction terms in rows 14–25. For example, the effect of *VCPROM* in the first period is 0.3682 which is significantly different from zero at a 5% level. The effect of *VCPROM* in the second period is the sum of the first period coefficient and the coefficient of *LATE* interacted with *VCPROM* (that is, *L_ VCPROM*). Thus the second period coefficient is 0.3682–0.5779 = −0.2097. The coefficient of *L_ VCPROM* is significantly different from zero at a 5% level signifying a change in the effect of *VCPROM* between the two periods. However, based on a standard *t*-test of whether the sum of two estimated coefficients is significantly different from zero we cannot reject the hypothesis that the sum is equal to zero. That is, the sum of the two coefficients (−0.2097) is not significantly different from zero; *VCPROM* has a statistically significant effect only in the early period.

With the exception of the coefficient on *PATENTS* (which is not significantly different from zero) all regressors for which we have priors regarding signs satisfy our priors. We drop interac-

Table 5
PROCEEDS regressions results: alternative models.

	Panel A			Panel B			Panel C		
	Coef.	*t*-Stat		Coef.	*t*-Stat		Coef.	*t*-Stat	
NOBEL	0.9511	3.39	***	0.7478	3.97	***	0.7678	4.23	***
PERCENT_SOLD	0.0186	0.14		0.0368	0.27		0.0264	0.19	
ALLIANCES	0.0517	2.09	**	0.0518	2.02	**	0.0625	2.51	**
ALL_SQ	−0.0030	−3.62	***	−0.0030	−3.46	***	−0.0034	−3.98	***
MGR_SHARE	0.0332	1.09		0.0304	1.00		0.0298	1.01	
R&D_EXPEND	0.3036	3.00	***	0.3185	2.83	***	0.3835	3.59	***
EMPLOYEES	0.1370	1.68	*	0.1448	1.89	*	0.1383	1.72	*
PHASE	0.0754	2.93	***	0.0811	3.15	***	0.0813	3.34	***
PATENTS	0.0172	5.29	***	0.0185	5.82	***	0.0201	5.78	***
PATENT_CITES	0.0046	1.76	*	0.0042	1.54		0.0077	2.65	***
VCPROM	0.3509	2.02	**	0.3691	2.04	**	0.3807	2.24	**
BIO_RATIO	−2.9181	−0.93		−2.2605	−0.74		−2.5236	−0.65	
L_NOBEL	−1.1044	−2.62	**	−0.7579	−2.02	**	−0.8457	−2.80	***
L_ALLIANCES	−0.0916	−2.33	**	−0.1254	−3.39	***	−0.1080	−2.97	***
L_ALLSQ	0.0041	3.67	***	0.0049	4.45	***	0.0046	4.30	***
L_R&D_EXPEND	−0.2129	−1.43		−0.1739	−1.16		−0.3153	−2.07	**
L_VCPROM	−0.5591	−2.23	**	−0.5965	−2.15	**	−0.5927	−2.42	**
L_BIO_RATIO	10.0794	2.67	***	9.9121	2.69	***	10.0306	2.16	**
NOBEL_AGE	−0.0346	−1.32							
L_NOBEL_AGE	0.0361	1.29							
REVENUES				−0.025	−0.64				
L_REVENUES				0.051	0.81				
AGE							−0.2375	−2.25	**
L_AGE							0.0844	0.81	
Observations	89			85			89		
R-Square	0.686			0.706			0.798		

	Panel D			Panel E			Panel F		
	Coef.	*t*-Stat		Coef.	*t*-Stat		Coef.	*t*-Stat	
NOBEL	0.6682	3.29	***	0.7873	3.92	***	0.7743	4.13	***
PERCENT_SOLD	0.0130	0.10		0.0095	0.06		0.0264	0.19	
ALLIANCES	0.0502	1.87	*	0.0514	2.00	**	0.0576	2.15	**
ALL_SQ	−0.0030	−3.50	***	−0.0029	−3.35	***	−0.0032	−3.36	***
MGR_SHARE	0.0416	1.34		0.0329	1.04		0.0286	0.99	
R&D_EXPEND	0.2287	2.15	**	0.2938	2.78	***	0.3090	3.25	***
EMPLOYEES	0.2060	2.20	**	0.1563	1.77	*	0.1486	1.97	*
PHASE	0.0825	3.57	***	0.0760	2.93	***	0.0782	3.17	***
PATENTS	0.0197	6.73	***	0.0178	5.59	***	0.0178	4.70	***
PATENT_CITES	0.0031	1.34		0.0045	1.76	*	0.0046	1.75	*
VCPROM	0.3114	1.69	*	0.3824	2.06	**	0.3529	1.99	**
BIO_RATIO	−1.9381	−0.54		−3.1072	−0.76		−3.0775	−0.72	
L_NOBEL	−0.6589	−2.10	**	−0.8791	−2.88	***	−0.8796	−2.64	***
L_ALLIANCES	−0.0820	−1.98	*	−0.0895	−2.27	**	−0.0965	−2.32	**
L_ALLSQ	0.0039	3.42	***	0.0040	3.49	***	0.0043	3.38	***
L_R&D_EXPEND	−0.1848	−1.26		−0.2135	−1.37		−0.2353	−1.67	*
L_VCPROM	−0.4497	−2.02	**	−0.5757	−2.36	**	−0.5471	−2.27	**
L_BIO_RATIO	9.0250	2.31	**	10.4914	2.28	**	9.4880	1.23	
TOTAL_CITES	0.0946	0.94							
L_TOTAL_CITES	−0.3167	−2.22	**						
MAX_CITES				−0.0574	−0.47				
L_MAX_CITES				0.0002	0.00				
CUM_BIOTECH							0.0049	0.67	
L_CUM_BIOTECH							−0.0013	−0.10	
Observations	89			89			89		
R-Square	0.715			0.685			0.686		

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

tion regressors which have *t*-statistics less than one since this strongly indicates that the second period coefficient is not different from the first period coefficient. The dropped regressors are *LATE*, *L_PERCENT_SOLD*, *L_MGR_SHARE*, *L_EMPLOYEES*, *L_PHASE*, *L_PATENTS*, and *L_PATENT_CITES*. Results are reported in the second panel of Table 4; we consider this model to be our "base" model.

The most striking result for the first window is the very large effect that having a Noble laureate (*NOBEL*) associated with the firm has on firm value. Based on the coefficient of *NOBEL* in the second panel of Table 4 (0.7474), and on the fact that the first period median value of *PROCEEDS* for firms without an affiliated Nobel laureate is $31.8 million, we can infer that the addition of a Nobel laureate to a non-Nobel firm would have been associated with an additional $23.8 million in IPO proceeds.

The signaling literature makes the point that the importance of a signal diminishes when other measures of firm quality become available, reducing uncertainty. We argue that the large differences in characteristics between first-window and second-window firms are an indication that more information regarding firm quality was available in the second period. Thus, we expect to observe dimin-

ished importance of signals of the underlying quality of a firm in our sample at the time of the IPO. Operationally and with respect to the signal provided by the presence of a Nobel laureate, the coefficient of *L_NOBEL* should be negative. A negative and significant coefficient is observed. Further, the sum of the coefficients of *NOBEL* and *L_NOBEL* is not significantly different from zero (p-value = 0.644). Thus our results suggest not only that the importance of the Nobel signal diminished as expected, but that its importance as a signal of value in the second period disappears. That is, in the second period when there are more substantial measures of firm quality (patents, products in phase trials, etc.) and the firms are more mature, the importance of the Nobel signal disappears.

The net effect of a few alliances is positive on proceeds, but the returns from adding additional alliances are decreasing. Combining the results for *ALLIANCES* and *ALL_SQ*, the implication is that after nine alliances the marginal effect of adding another alliance is negative. At the median of *PROCEEDS* for first window firms the addition of the first alliance adds around $1.6 million to firm value and the second alliance adds around $1.4 million. The interaction of *LATE* and *ALLIANCES* (*L_ALLIANCES*) is negative and significant but the sum of the coefficients of *ALLIANCES* and *L_ALLIANCES* is not significantly different from zero (p-value = 0.192). It is also the case that the sum of the coefficients of *ALL_SQ* and *L_ALLSQ* is not significantly different from zero. Thus, the statistically significant effect of the number of alliances on proceeds in the first period disappears in the second period.

Finally, in the first period there is a positive and significant coefficient for *VCPROM* indicating that the prominence of the venture capital partners was a positive signal. However, the coefficient of *L_VCPROM* is negative and significant and the sum of the coefficients of *VCPROM* and *L_VCPROM* is not significantly different from zero (p-value = 0.266).

The results are clear with respect to signals. In the first period a Nobel laureate associated with the firm conveys a strong positive signal to potential investors regarding the future prospects of a firm. This also holds for alliances and the prominence of the venture capital partners in the first period. In the second period the firms were generally further along in the commercialization process as evidenced by the number of products in phase trials and the number of patents, metrics that have been shown elsewhere to be valid predictors of firm value. Consistent with the signaling literature we find that the added presence of these measures of firm value reduces the importance of signals in the second period while the importance of more substantive information increases.[15]

6.2. Alternative models

There is substantial variation in the elapsed time between the date the Noble Prize was awarded and the date of the public equity offering. For the early window, 7 laureates had been awarded their prize within 7 years of the equity offering; one had received the prize 16 years prior. The average number of elapsed years was 5.75. In the later window, only 2 Nobel prizes had been awarded within the prior 7 years. Four prizes were awarded more than 23 years before the equity offering and one was awarded 42 years prior to the equity offering, for an average elapsed number of years of 23.29. The mean years elapsed are statistically significantly different between the two periods (p-value = 0.021). To capture any time depreciation in the value of a Nobel to the success of a firm we include the product of the indicator of the presence of a Nobel laureate and the number of years since receiving the award. Variable *NOBEL_AGE* modifies the effect of *NOBEL*; the effect of a Nobel laureate becomes the coefficient of *NOBEL* plus the coefficient of *NOBEL_AGE* times the number of elapsed years since receiving the award. We expect *NOBEL_AGE* to modify downward the expected positive effect of *NOBEL* on valuation.

Results are reported in Panel A of Table 5. The coefficients of *NOBEL_AGE* and *L_NOBEL_AGE* are neither individually nor jointly different from zero. The coefficient of *NOBEL* increases from 0.7474 to 0.9511. There continues to be no statistically significant Nobel effect in the second period, and the importance of the alliance and venture prominance signals also disappears in the second period. The effects of the other variables on proceeds are unchanged.

Although we questioned the validity of revenues as a predictor of firm value, nonetheless, and as a check, we include the log of the total revenues received by the firm in the 3 years prior to the IPO (*REVENUES*) as well as revenues interacted with *LATE* (*L_REVENUES*). Since the data are in logs, this is less restrictive than entering the log of the ratio of R&D to revenues.[16] Results are in Panel B of Table 5. The coefficient of these new regressors are neither individually nor jointly significantly different from zero. The other coefficients are almost identical to what is presented in Table 4; in particular, the effect of the signals does not change. The only difference of note is the fact that the sum of the coefficients of *ALLIANCES* and *L_ALLIANCES* is significant and negative in the second period and the sum of *ALLSQ* and *L_ALLSQ* is significant and positive.

We include the age of the firm in months at the time of the IPO (*AGE*) and *AGE* interacted with *LATE* (*L_AGE*). Results are reported in Panel C of Table 5. The coefficient of *AGE* is negative and significantly different from zero. This result is counterintuitive. However, the results for the other regressors are only slightly different from those for the base model; in particular, the effect of the signals does not change. To examine whether there are any effects between firm age and signals we considered interactions of firm age with *NOBEL*, *ALLICANCES* and *VCPROM*. Only the interaction between *AGE* and *ALLICANCES* is significantly different from zero (and negative). The effects of the variables in the base model continue to hold. For the sake of brevity we do not include these regressions.

Each Nobel laureate is associated with a university. This raises the possibility that the value of a Nobel is, at least in part, a reflection of a tie to a university. As a measure of the reputation of all university-affiliated scientists working with the firm, we included the log of the total number of citation (*TOTAL_CITES*) these university researchers had received to their prior research at the time of the offering. We also include its interaction with *LATE* (*L_TOTAL_CITES*). Results are in Panel D of Table 5. The coefficient of *TOTAL_CITES* is positive but insignificant and the result for *L_TOTAL_CITES* is counterintuitive in that it is negative and significantly different from zero. The other coefficients are very similar to those of the base model; in particular, the effect of the signals does not change.

We include in the base model the log of the maximum number of citations (*MAX_CITES*) received by any of the university scientists (including the Nobel laureates) as well as its value interacted with *LATE* (*L_MAX_CITES*). This should provide an indication of whether the Nobel effect is simply a "star scientist" effect or whether there is some special importance to the presence of a Nobel. Results are reported in Panel E of Table 5. The coefficients are neither individually nor jointly different from zero. The other results are very similar to those of the base model; in particular, the effect of the signals does not change.

[15] While the coefficients of the substantive variables such as *PHASE* and *PATENTS* do not change between periods their importance to *PROCEEDS* increases since the magnitudes of the regressors increases. For example *PATENTS* increases from an average of 0.5 in the first period to an average of 6.64 in the second.

[16] That is, we relax the restriction that the coefficients of the log of revenues and the log of R&D expenditures are equal in absolute value.

This industry was relatively new at the beginning of the first window and still somewhat new even by the end of the second period. Some accounting for industry maturation over this period might, therefore, be informative. We choose to measure this maturation as the cumulative number of biotechnology IPOs (*CUM_BIOTECH*) that had taken place prior to a particular IPO event. For example, Biomatrix Inc. went public at the end of June 1991. By that time there had been 18 prior IPOs during the first window; thus *CUM_BIOTECH* takes the value 18 for this observation.[17] It is our expectation that *CUM_BIOTECH* will have a positive coefficient since a larger value indicates a more mature industry at the time of the IPO and thus the availability of more information about the industry to investors. We also add the interaction of *LATE* and *CUM_BIOTECH* (*L_CUM_BIOTECH*). Results are reported in Panel F of Table 5. Neither *CUM_BIOTECH* nor *L_CUM_BIOTECH* are significantly different from zero. Again we find very little change in the other coefficients; in particular, the effect of the signals does not change.

It is possible that signals have dependent effects either as substitutes or complements. While the number of observations makes such an examination problematic, we estimated a series of regressions in which we interact *NOBEL* with *ALLIANCES* and *VCPROM*. We also included these interaction variables interacted with *LATE*. We considered five regressions differentiated according to the set of interactions included in a regression – one regression included all interactions. In every case the coefficients of the interaction terms were not jointly different from zero so that we are unable to uncover any dependent effects. For the sake of brevity we do not include the detailed results of the five regressions.

6.3. Alternative dependent variables

Earlier we noted that the choice of dependent variable is not obvious. Our choice of *PROCEEDS* was based on the importance of the firm's ability to acquire additional resources for what is generally a long, expensive development process. Other possible choices include the pre-money valuation of the firm (Stuart et al., 1999), the total value of the firm on the day of the IPO and that portion of the firm's value that is not sold via the IPO. We computed four alternative measures of value and then regressed each of these measures on the regressors in our base model. The alternative measures are: (1) the value of the shares sold based on the end-of-day price on the day of the IPO (number of shares sold times the final day one price); (2) the value of the company based on the opening price; (3) the value of the company based on the final price; and, (4) the value of the unsold shares based on the opening price and the value of the unsold shares based on the final day one price.

Substituting these various measures for the dependent variable results in few differences from the ones presented in Table 4. The only differences of note are that the coefficients of the number of alliances and the square of the number of alliances tend not to be significantly different from zero and the regressions that include the final day one price often have smaller *t*-statistics. This latter result is not surprising since the end of day prices are subject to issue of underpricing and hence there is greater noise in the outcomes. The important result that the statistical significance of signals disappears in the second period continues to hold with these new measures of the dependent variable; in particular, the coefficient of *NOBEL* is positive and significant in the first period but the signal value of NOBEL disappears in period two. For the sake of parsimony we do not provide the details.[18]

[17] We do not have the number of biotechnology IPOs prior to the first window, but this is not a problem since adding that to each *CUM_BIOTECH* observation will not change the results (except for the regression constant term).

[18] Results are available upon request.

7. Discussion and conclusion

Managers of small, entrepreneurial firms are faced with the difficult task of trying to signal the value of their firms when raising money. To meet this challenge, firms in emerging industries often rely on non-financial metrics as a signal of value. Here we examine the role that scientific status plays in signaling quality. Specifically, we argue that the presence of a Nobel laureate affiliated with a firm making an IPO provides a signal of firm quality to potential investors. Moreover, and building on the work of Podolny and Scott Morton (1999) and Stuart et al. (1999) we hypothesize that the importance of status diminishes as other measures of firm quality become available. We test our hypothesis for two periods of initial public offerings in biotechnology: 1990–1992 and 1996–2000. We document that there is clear differences in the maturity of the firms across the two windows on a number of key metrics. This change in maturity is consistent with a variety of hypotheses including Pisano's (2006) view that investors in biotechnology became more cautious leading to delayed investment until firms demonstrated more tangible research output. Alternatively, firm maturity could simply follow from the long closure of the biotechnology window in the mid 1990s so that firms made IPOs at a later stage of development in the late 1990s.

Our results suggest that a Nobel laureate served as a powerful signal of firm value during the first window when the firms going public were less established in terms of number of patents, products in clinical trials, etc. To wit, the presence of a Nobel laureate during our early period is associated with additional IPO proceeds of about $24 million in comparison to offerings without a Nobel affiliate. In our second period, firms were more "mature" based on a variety of measures (patents, numbers of products in clinical trials, etc.). The signaling literature is clear in suggesting that the value of the signal is diminished in the presence of other measures of quality. Our results are in line with this prediction. Not only does the presence of a Nobel laureate lose its value in the second period, but we also find a change between the two windows in the importance of other non-financial metrics used to convey value.

Our research makes important contributions to the literature. We are the first to examine the role that scientific status plays in initial public offerings. Our research also suggests that in nascent markets audiences may initially look to seemingly credible signals inherited from other fields, even those whose accuracy might be quite low. More importantly, while our work is consistent with that of Podolny and Scott Morton (1999), it differs in that we consider entrants into an emerging industry while they consider entrants into an established industry. In their setting status signals facilitate the acceptance over time of new firms by "mature" firms. In our setting status signals, at least initially, facilitate the success of an IPO by new firms in an emerging industry. The importance of status signals diminishes as the industry accumulates experience and the firms going public are more "mature." We do not know nor does our data allow us to determine the causality between firm and industry maturity; thus we cannot determine whether the diminished importance of signals is due to reductions in industry or firm level uncertainty. The finding of a change in the relative importance of non-financial metrics used as signals of quality is important since this is one of the first pieces of research to examine the dynamic nature of signals.

Our research leaves at least two question unanswered. First, there is the disentangling of firm versus industry uncertainty in an emerging industry. Second, there is the question of whether the results would hold for firms in other high tech industries making an initial public offering. We leave these questions to future research.

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