Journal of Business Venturing xxx (2009) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Venturing

The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology start-ups[☆]

Yanfeng Zheng[a,1], Jing Liu[b,2], Gerard George[c,*,3]

[a] Clemson University, 117c Sirrine Hall, Dept. of Management, Clemson, SC 29634, United States
[b] Cornerstone Research, 599 Lexington Ave., New York, NY 10022, United States
[c] Imperial College, Business School, South Kensington, London SW7 2AZ, UK

ARTICLE INFO

Article history:
Received 26 September 2009
Received in revised form 23 January 2009
Accepted 13 February 2009
Available online xxxx

Keywords:
Capabilities
Absorptive capacity
Alliances
R&D
Valuation

ABSTRACT

Prior research suggests that a high technology start-up's innovative capability and inter-firm network influence its performance and consequently, firm valuation. Few studies consider their joint influence and even fewer consider the temporal change of those effects on firm valuation. In this study, we propose that firm age, a key organizational variable, represents both the development of organizational routines from a start-up's perspective and the accumulation of accessible information from an investor's viewpoint. As such, an investor's evaluation of a high technology start-up's innovative capability and inter-firm network evolves with firm age. Using panel data of 170 biotechnology start-ups, our results suggest that the relative value of network status declines while the impact of innovative capability increases with firm age. Interestingly, there is a growing complementary effect of innovative capability and network heterogeneity on firm valuation. The implications of these findings for entrepreneurial practice and theories of firm capabilities and inter-firm network are discussed.

1. Executive summary

Technology start-ups with high growth potential tend to be resource-constrained and often require infusion of financial capital. To do so, investors and entrepreneurs will arrive at an estimate of the market value or "valuation". The valuations that investors place on start-ups will influence the proportion of equity shares disbursed to raise adequate funds to ensure firm growth and survival. Consequently, both entrepreneurs and investors consider valuation to be an important metric that determines their equity proportion and their financial returns from investing into the venture. Therefore, understanding the factors affecting new ventures' valuation is an issue of substantial importance.

We maintain that investors will examine information on a start-up's innovative capability and inter-firm network to arrive at an estimate of its financial value. Information suggesting superior innovative capability and external connections increases the confidence of investors placed on the start-ups. Prior studies have provided some evidence that innovative capability and inter-firm network attributes are positively correlated with higher firm valuation for new ventures. Whereas studies confirm the positive linkage between both kinds of information and firm valuation in start-up context, there are gaps in our understanding of the combined effect between innovative capability and inter-firm network and more importantly, the temporal change of those effects. Do investors value the potential complementary effect between innovative capability and inter-firm network? Does one kind of information become more important, or stated differently, does its value impact increase with firm age? In this study, we posit that

☆ The views and opinions expressed herein are those of the authors, and should not be attributed to Cornerstone Research.

* Corresponding author. Tel.: +44 20 7594 1876.
E-mail addresses: yanfenz@clemson.edu (Y. Zheng), jliu@cornerstone.com (J. Liu), g.george@imperial.ac.uk (G. George).
[1] Tel.: +1 864 656 1573.
[2] Tel.: +1 212 605 5405.
[3] The third author gratefully acknowledges the support of the ESRC Advanced Institute of Management Research Fellowship (ESRC RES-331-27-0011).

0883-9026/$ – see front matter © 2009 Elsevier Inc. All rights reserved.
doi:10.1016/j.jbusvent.2009.02.001

firm age represents two processes critical to investors' evaluation—routine development and information accumulation. Hence the influences of innovative capability, inter-firm network and their interaction on firm valuation vary when start-ups grow older.

Using panel data of 170 biotechnology start-ups over 15 years, our study indicates that the value impact of network status declines while the value impact of innovative capability increases with firm age. In addition, there is a strong and growing complementary effect of innovative capability and network heterogeneity on firm valuation. Our results suggest that different kinds of information and their interaction present themselves differently in investors' eyes as start-ups grow older.

Technology start-ups facing complex environments have to make critical decision in terms of allocating their scarce resources and invest to build either internal capabilities or external partnerships. Our study suggests that the timing of these resource decisions is a significant factor that both entrepreneurs and investors need to consider. We find that whereas innovative capability and external connections are valuable to new ventures, inter-firm network tends to be more important for valuation purpose at earlier phases of their life. In later years, investments in building technological capabilities have stronger value enhancing impact. The study's findings provide entrepreneurs, investors and managers in technology companies a more precise understanding of how both types of resources change dynamically to impact firm valuation.

2. Introduction

Technology-based new ventures often need to secure significant amount of financial resources from investors to further develop their technologies into marketable products. Investors assign a market value or valuation to the venture and then proportionally take an equity position based on the size of their investment and the agreed valuation. A key problem in assigning a valuation to the high technology start-up is the tremendous uncertainty associated with its quality. Consequently, investors rely on information that may reveal the quality of the venture including technological capabilities, corporate governance setup, private placements, and partnerships with other firms among others (Chang, 2004; Deeds and Decarolis, 1997; Janney and Folta, 2003; Sanders and Boivie, 2004; Stuart et al., 1999).

In this study, we focus on two types of information: internally-generated information on the start-up's innovative capability and externally-verifiable information on the start-ups inter-firm network attributes. Both these sources of information are likely to influence an investor's perception of firm value. There is an emerging and rich discussion of firm capabilities, their origin, evolution and consequences in the strategy literature. This stream of research suggests that heterogeneous capabilities lead to systematic performance difference among firms because capabilities are valuable, hard to imitate and obtain on resource market (Cockburn et al., 2000; Teece et al., 1997). Hence, high technology start-ups with superb innovative capability are valued positively by investors because they are perceived to have higher prospects for generating commercially successful products and sustaining their competitive advantage (DeCarolis and Deeds, 1999). Similarly, organizational scholars have extensively documented the positive impact of inter-firm network (or alliances) on firm performance. This literature posits that since information and other strategic resources are unevenly distributed in the market, firms need to reach beyond their organizational boundaries to secure the resources critical to developing and maintaining competitive position (Baum et al., 2000; Burt, 1992; Powell et al., 1996). In absence of accurate information on start-ups, investors even rely on prestige of partners to infer the quality of start-ups (Stuart et al., 1999). As a result, investors often respond to alliances with other firms who possess complementary resources such as financial, research and marketing capabilities positively (Chang, 2004; Lavie, 2007). Together, the extant literature suggests that investors interpret both kinds of information positively when evaluating the firm valuation of high technology start-ups.

Theoretically, there are gaps in our knowledge of the effects of innovative capability and inter-firm network on firm valuation of start-ups. Prior studies tend to focus on either kind of information but rarely examine their combined influence. Of particular interest to strategy scholars is the complementary effect between innovative capability and inter-firm network (Lavie, 2006; Zaheer and Bell, 2005). Whether investors appreciate such synergistic effects to estimate firm value remains an unresolved issue. An even more pressing question arises with regard to the age-related effects of innovative capability and inter-firm networks on firm valuation, which leads us to the research question: *how do the effects of innovative capability and inter-firm network attributes on valuation vary with firm age?* It is likely that there may be shifts in the relevance and the emphasis placed by investors on information as the firm grows older. This study addresses these gaps by offering a theoretical account of the combined effect of innovative capability and inter-firm network and more importantly, their age-related effects on firm valuation.

3. Theory and hypotheses

3.1. Dynamic impact of innovative capability

There is some collective evidence to show that innovative capability is highly correlated with growth potential and long term performance of high technology start-ups. We define innovative capability as the ability to generate novel and useful knowledge or products (Hagedoorn and Cloodt, 2003; Lee et al., 2001). Innovative capability is crucial for technology start-ups who often achieve competitive advantage by delivering new products to the market. Lee et al. (2001) found a positive relationship between innovative capability and sales growth using data on 137 Korean technology start-ups. Other studies reach a similar conclusion that start-ups' innovative capability positively influences the likelihood of developing new products and improving financial performance (e.g. Deeds and Decarolis, 1997; George et al., 2002; Shan et al., 1994). In practice, equity analysts and investors often place great emphasis on innovative capability to make valuation decisions (Bogdan and Villiger, 2008). Below, we develop arguments to suggest that the influence of innovative capability on firm valuation increases with firm age.

First, firm age represents development of organizational routines, procedures and policies that have profound consequences on organizational behaviors. Organizational scholars have attributed lack of reliable and semi-automatic routines as one key reason why young firms are more likely to fail, often called the “liability of newness” (Freeman et al., 1983; Stinchcombe, 1965). When high technology start-ups grow older, they develop rules, routines and policies that enable them to cope with the uncertainty embedded in new ventures. It is often considered as the result of organizational learning from either own experience or others' experience (Klepper, 2001; Levitt and March, 1988). The existence of such organizational routines, procedures, and policies are, in general, beneficial for technology start-ups. For example, organizations may develop procedures for maintaining, organizing and reporting research records either form their own operations or by imitating others (Mowery et al., 2002). Those procedures provide for improved protection of their intellectual property and facilitate research and communication. Consequently, for two start-ups with comparable levels of innovative capability, the older firm with more robust routines is likely to extract greater economic value from its innovations than the younger firm with fewer routines in place.

Second, from an investor perspective, firm age also captures information accumulation by providing an accessible and verifiable track record for investors. It is widely accepted that new venture valuation is rife with uncertainty primarily due to lack of historic records or verifiable claims made by new ventures (Sanders and Boivie, 2004; Stuart et al., 1999). When technology start-ups grow older, though, they generate more information either intentionally or involuntarily. For instance, they may present their scientific discoveries at academic conferences or demonstrate new products at industry exhibitions. Information about start-ups, their activities, and successes also circulate in investor communities that tend to be tight, close knit groups which operate predominantly through investment syndicate networks or personal ties (Sorensen and Stuart, 2000). Therefore, the older a technology start-up, it becomes more likely that potential investors can access relevant information. Such information accumulation will help alleviate the information asymmetry problem surrounding a start-up's valuation, especially when assessing novel technologies.

Therefore, for two start-ups with comparable level of innovative capability, investors will tend to value the older start-up higher by reducing the valuation discount associated with uncertainty. For example, Vertex Pharmaceuticals filed its first patent only one year after its incorporation. Due to the lack of understanding of its novel “rational drug design” technology and uncertainty surrounding its internal operations, investors placed a conservative valuation on Vertex. Aastrom Bioscience, founded around the same time as Vertex, also filed one patent when it was four years old. With comparable novel stem cell technology, Aastrom Bioscience, however, was able to get a favorable valuation from its investors, due to its relative maturity and because better information is accessible by the investors on the firm and its innovative capability. In sum, investors are willing to place higher valuation on an older start-up than a younger one with equal level of innovative capability because they perceive that the older firm is more likely to leverage its innovative capability to achieve commercial success. Therefore, we posit that:

Hypothesis 1. The positive effect of innovative capability on firm valuation will increase with firm age for high technology start-ups.

3.2. Dynamic impact of inter-firm network

The inter-firm network literature offers an alternative perspective that highlights the external network's impact on firm performance (Gulati, 1998; Powell et al., 1996). Inter-firm networks or strategic alliances are defined as voluntary arrangements between firms involving exchange, sharing or co-development of products, technologies, or services (Gulati, 1998). Whereas multiple benefits have been associated with a firm's external connections, there are two fundamental benefits that accrue to the focal firm: the “transferred” benefit and the “perceived” benefit, corresponding to the “pipes” and “prisms” metaphor proposed by Podolny (2001). On the one hand, a tie between two firms can be considered as a pipe transferring information and other resources between the two. On the other hand, the presence of the tie is also an informational cue on which other players rely to make inferences about the underlying quality of one firm (Podolny, 2001:34). Building on this insight, we focus on two inter-firm network attributes—network heterogeneity and network status to capture the two benefits respectively.

First, considering the inter-firm network as an important channel through which technology start-ups exchange information and other resources with their environment, the more heterogeneous their networks, the more diverse information and other resources they could receive from other participants in the industry. For technology startups operating in rapidly changing environments, to be competitive requires not only developing effective in-house innovative capabilities but also access to a diverse information and resource pool to keep abreast of technological and institutional changes. Prior studies have demonstrated that network heterogeneity helps high technology start-ups grow and prosper (Baum et al., 2000; Powell et al., 1996). With such understanding, investors often value start-ups with heterogeneous connections or portfolios of partners positively (Chang, 2004; Lavie, 2007).

Our main focus, though, is to investigate how investors value network heterogeneity of startups as a function of their age. We maintain that holding other things equal, investors will value an older start-up higher than a younger one with the same level of network heterogeneity. Following from our discussion in the previous section, firm age captures the relative robustness of routines developed by the start-up that enables it to cope with uncertainty more effectively, be it routines for internal innovation (Zahra and George, 2002) or external collaboration (Kale et al., 2002). Start-ups can also learn how to develop effective partnerships with other informational sources such as functional experts or industry-specific consulting firms. Amgen, a leading biotechnology firm, gradually developed procedures to conduct due diligence on selecting and handling partners based on its early years of experience with alliances (Binder and Bashe, 2008). Firms are likely to differ in how much value they extract from these collaborations. The strategic alliance literature has provided systematic evidence that alliances do not benefit participant firms automatically and they need to learn how to deal with inter-firm differences such as conflict of interest, culture and even differences in infrastructure (Anand and Khanna, 2000). Older start-ups, assisted with tacit or explicit rules, procedures and policies, are likely to extract higher value than younger ones with similar collaborations. Stock markets also respond to experienced firms more positively than inexperienced ones when they make similar collaboration announcements (Anand and Khanna, 2000; Kale et al., 2002). From an investor's perspective, they also have more opportunities to collect information about how start-ups deal with their partnerships when they grow older, where the internal routinization and learning outcomes are more visible to outside investors. On average, investors are willing to believe those older start-ups are able to handle partnerships better than their younger counterparts because the investors collect more information in this regard. In sum, we propose that:

Hypothesis 2a. The positive effect of network heterogeneity on firm valuation will increase with firm age for high technology start-ups.

When faced with uncertainty and incomplete information about technology start-ups, investors may rely on prestige of their partners to infer their quality. Such endorsement or signaling effect is well documented in firm valuation literature (Carter and Manaster, 1990; Stuart et al., 1999). This body of research suggests that start-ups having affiliations with prominent endorsers tend to outperform those without such relationships in terms of time to initial public offering (IPO) and raising more capital at IPO. We argue that the magnitude of this positive impact of network status on firm valuation will decrease with firm age.

First, network status, if understood as a social cue or secondary information used to infer the quality of start-ups, benefits little, if at all, from internal routine development. In fact, partnering with prestigious partners could be detrimental to older start-ups with established routines and strategies because their powerful partners may demand changes disruptive to operations of start-ups (Alvarez, 2001). Rond (2003) documented a partnership between Rummidgen, a new founded biotech firm and Plethora, an established pharmaceutical company (real story with pseudo names). Though Rummidgen benefited initially from the endorsement from an established organization, it became increasingly frustrated with its established partner because its partner changed the focus of the partnership unexpectedly twice and interfered with its internal research.

Further, the value of endorsement or the associated signaling effect is likely to taper off. As start-ups release more relevant information to investors by making progress with product development or in attaining investor-set milestones or through other channels such as academic conferences or presentations to potential investors, network status becomes less critical than it was in the early stages of the start-up's life. As such, investors may eventually embrace primary information related to firm quality instead of secondary information such as prestige of partners to make valuation decisions (Sanders and Boivie, 2004; Stuart et al., 1999). Shaman Pharmaceuticals, for example, enjoyed an initially hefty valuation from its partnerships with large pharmaceutical companies and prominent investors such as Microsoft cofounder Paul Allen. However, as the firm progressed, its technological limitations were revealed and investors reduced their expectation. The firm's valuation sank even with prestigious collaborations after years of development. Here, we posit that the status signal or “prism” effect of inter-firm network decreases with firm age because investors gain a better understanding of the focal start-up and rely less on the endorsement effects of prestigious partners. Therefore, we propose that:

Hypothesis 2b. The positive effect of network status on firm valuation will decrease with firm age for high technology start-ups.

3.3. The complementarity of innovative capability and inter-firm network

The value of a firm's internal resources may be amplified with the presence of connections with external organizations (Lavie, 2006). Firms with superb innovative capability are better prepared to assimilate external information and allocate resources correspondingly (Cohen and Levinthal, 1990). A heterogeneous network provides access to diverse and effective information flows and, consequently, provides the opportunity to absorb external information. Zaheer and Bell (2005) found that firms with desirable network positions alone are unable to exploit structural benefits. However, those innovative firms combined with desirable network positions are most likely to develop new products, a notion consistent with the complementarity of innovative capability and inter-firm network. Thus, the extant literature makes a case that firms with higher internal innovative capability are more likely to utilize their diverse network access and transform it into higher firm value by pursuing technological opportunities and responding to market and competitive shifts.

Questions remain on how this complementary effect between innovative capability and network heterogeneity changes with firm age. The organizational learning literature suggests that firms develop organizational routines to cope with their internal and external environments (Levitt and March, 1988). Firm age can be viewed a proxy for the development of organizational structures and routines to support behaviors such as collaborative partnerships or innovation. At a younger age, technology start-ups with both innovative capability and favorable network positions are less likely to fully realize the combined potential because of resource constraints or lack of corresponding organizational structures or support. Consequently, the complementary effect is likely to increase with the presence of organizational routines, infrastructure or even awareness to assimilate external resources (Sorensen and Stuart, 2000). The alliances formed by start-ups may also stem from expedient needs such as access to financial resources or specific technological knowledge. With experience, the firm also develops a capability to strike a balance between their external collaborations and in-house research (Kale et al., 2002; Rothaermel and Deeds, 2006). Additionally, investors are likely to perceive the innate synergistic effect with a track record of success and, consequently, place higher value for an older start-up than a younger one with a similar opportunity. From a value creation perspective, the complementary effect between innovative capability and network heterogeneity will likely be stronger when a high-technology start-up becomes more mature and mindful regarding the alignment between internal capability and its network position. Therefore we postulate:

Hypothesis 3. The positive complementary effect of innovative capability and network heterogeneity on firm valuation will increase with firm age for high technology start-ups.

4. Method

4.1. Sample

Biotechnology refers to the manipulation of genetic material through recombinant DNA technology, cell fusion and monoclonal antibodies. Under this definition, the biotech industry covers firms specializing in the human diagnostics and therapeutics (Stuart et al., 1999). The biotechnology industry represents an ideal research setting to test our hypotheses for several reasons. First, forming strategic alliances has become a common practice in the biotechnology industry (Powell et al., 1999). Virtually every biotech firm is involved in several partnerships with other biotech firms, pharmaceutical companies, or research institutes. Also, the capability to produce new knowledge is a critical factor for survival and success of biotech start-ups. The co-existence and importance of innovative capability and inter-firm network for biotech start-ups make it an ideal research context for our study. Additionally, the past two decades have witnessed a phenomenal increase in interest in the biotechnology industry among researchers, practitioners and policy makers. Consequently, data on biotech firms such as performance and partnering behavior have become readily available.

In this study, we took multiple steps to identify sample firms. First, we checked Bioscan, a comprehensive biotechnology industry directory, to identify firms that were active in human diagnostics and therapeutics and founded between 1983 and 1994. We chose firms founded in this period of time because we were unable to validate information for older firms and obtain information on new firms due to our panel data design. We also collected firm level data such as geographic location and firm size from Bioscan. This procedure generated over 500 U.S. based dedicated biotechnology firms. Patenting information was collected from the NBER patent database, which provides comprehensive coverage on three million US patents issued from 1969 to 1999 (Hall and Ziedonis, 2001). For alliance and valuation data, our primary data source was *rDNA.com* (formerly *Recombinant Capital*), a fee-based data access service and a leading biotechnology data provider. We complemented our data with other sources including *The GEN Guides to Biotechnology Companies*, LEXIS-NEXIS, SEC filings and company websites. After matching data with each source, the final sample size reduced to 170 dedicated biotechnology firms (DBFs). We tracked these firms from their founding years to 1999. In total, we created a panel with 1725 observations for model estimation.

4.2. Dependent variable

Firm valuation is the total market value of the company's equity. It was operationalized as the product of its shares outstanding and the price per share at the conclusion of a financing round. When a start-up experiences a financing event (e.g. venture capital investment or private placement) it will negotiate with investors on the market value of the firm. Our data contains 2524 financing rounds for 170 firms. On average, there are 1.3 financial rounds for each firm-year observation. To create a panel data on annual basis, we took following steps: 1) if a start-up had only one financial event at year t, we used its valuation for that year; 2) if a start-up had more than one financial event, we used the average valuation for that year; and 3) if a start-up had no financing event in year t, we used linear extrapolation to obtain the valuation data for year t. We used post-money valuation or post investment valuation because it is comparable to public market value for traded firms (Nicholson et al., 2005).

For start-ups, valuation is a more accurate firm performance measure than other financial measures because biotech start-ups typically do not generate stable revenues such that common financial measures (e.g. P/E ratio) are inaccurate indicators of performance or value. In practice, it is of great interest for the shareholders and investors to evaluate the true value of the focal start-up. For entrepreneurs, their economic returns hinge on how markets value their firm. For investors, firm valuation has a direct effect on their equity stakes and consequently their investment risk and returns. From a theoretical viewpoint, entrepreneurship scholars emphasize wealth creation where firm valuation can serve as a close proxy to measure how much wealth is being created.

Our primary source of valuation data was rDNA.com (formerly known as Recombinant Capital or ReCap). rDNA.com collects valuation records based on each biotech start-up's financing history and its valuation data are argued to be more accurate and comprehensive than other sources (Hand, 2007). Nevertheless, to ensure validity of the valuation data, we cross-checked a sub-sample of the firms with other sources: *Compustat* for publicly traded firms and *Venture Economics* for privately held firms. Both sources confirmed the reliability of the rDNA data. We used a logarithmic transformation to control for the skewness of the distribution (Lavie, 2007).

We treated valuation of a financing event as the proxy of the valuation for an entire year. We opted for this treatment because valuations are discrete events for privately held firms; i.e. valuation is assigned only when there is an investment occurring or other significant financial events. Hence, it might be that our treatment is crude to capture the nuances in the change in firm value within a year. To test the robustness of this treatment, we replaced valuation records with public market values whenever they are available (e.g. if a start-up became publicly traded). The public market valuations are the average of 12 end-of-month daily values of corresponding years and ought to be a more accurate measure of firm valuation for the whole year (Lavie, 2007). Our results are robust to the replacement of valuation data with public market values. We report the results based on discrete data.

4.3. Independent variables

Innovative capability can be gauged from various angles. Due to its complexity, comprehensive survey data are preferred to capture the multiple facets of the construct. Nevertheless, in our research context, it is infeasible to conduct a survey over time. Indeed, previous studies using archival data derived a capability measure from observable data (Helfat and Lieberman, 2002).

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

Patents are often treated as the proxy of underlying firm ability to generate new knowledge. Given that our context is the biotechnology industry, a knowledge intensive and competitive field, using patents as proxy of innovative capability is appropriate (Ahuja and Katila, 2001; Stuart et al., 1999).

Innovative capability was measured by the number of patents granted to the start-up between year t and $t-3$ and weighted by its forward citations to account for impact of patents. We determined the date of each patent by its filing rather than granted date since filing dates reflect the timing of inventions more accurately. To ensure that our analysis is not sensitive to the single measure, we also created an alternative patent-based measure which counts the number of patents with above average level forward citations, where the average is computed for the entire patent population in specific technical classes. Our empirical results do not change materially with respect to the two different measures. We report results associated with citation weighted patent measure.

We constructed two variables to capture the corresponding inter-firm network attributes. First, we measured *Network Heterogeneity* with a Herfindahl index of heterogeneity in types of partners such as biotech firms, pharmaceutical companies, universities, research institutes, and hospitals (Baum et al., 2000).

$$\textit{Network Heterogeneity}_{it} = \left[1-\sum\nolimits_{ij}\left(PA_{ijt}\right)^2\right] / NA_{it}$$

where PA_{itj} is the proportion of all start-up i's alliances that are with partner type j at time t, and NA_{it} is start-up i's total number of alliances at time t. A start-up with five alliances, two with pharmaceutical companies, two with biotech firms, and one with university would score $[1-(2/5)^2+(2/5)^2+(1/5)^2]/5=.124$. In fact, this measure is a simplified ego network measure. To access the robustness of this measure, we also created an alternative measure of network heterogeneity based on structural hole rationale (Burt, 1992). Specifically, we obtained the firm's ego network constraint values by using UCINET 6 (Borgatti et al., 2002) and timed the constraint value with -1 to simplify interpretation (Zaheer and Bell, 2005). Though the two measures differ in values, they produce qualitatively similar results. We report the results of Herfindahl index measure.

Network Status was measured as the number of agreements with prestigious partners that are top pharmaceutical companies or medical schools. We collected the rankings of pharmaceutical and medical schools from one major industry journal—*Pharmaceutical Executive* and *U.S. News and World Report* respectively (refer to Appendix A). We constructed a group of top pharmaceutical companies or medical schools based on their average ranking records.

Following common practice in alliance research (Podolny et al., 1996), both network-based variables were computed on a 3-year backward moving window rather than an annual basis to account for the duration of each alliance. We also conducted sensitivity analyses to ensure our results were robust to other specifications such as two or four year window.

4.4. Controls

4.4.1. Market condition

The biotechnology industry is sensitive to stock market conditions. Optimal stock market conditions suggest that the industry as a whole looks attractive to public investors and may inflate firm valuations. Conversely, an adverse market may force technologically competent firms to have deflated values. We used the biotechnology stock market index developed by Lerner (1994a) to account for the impact of market conditions on valuation.

4.4.2. Biotech firm density

Population density could be viewed as a proxy of industry competition, which may potentially reduce performance due to fierce competition on limited financial resources and research opportunities (Hannan and Freeman, 1977). From investors' perspective, the existence of a large number of competing firms gives them the option to leverage across firms innovating on similar products. To allow for this impact, we counted the number of biotech firms each year from Bioscan including not only dedicated biotech firms but also subsidiaries, foreign firms and spin-offs to precisely capture the population density effect.

4.4.3. Geographic area

Researchers argue that agglomeration economies and knowledge spill-over effects may be important in developing capabilities and, possibly firm valuation (DeCarolis and Deeds, 1999). California and Massachusetts account for almost 40% of US-based biotechnology firms (Burrill, 1992). Not surprisingly, geographic access may have a substantial impact on firm performance. Firms located in biotech populated areas are more likely to access leading edge knowledge, meet potential exchange partners and recruit talented scientists. To control for this geographic effect, we created two categorical variables to indicate whether a start-up is located in CA or MA areas (1 = yes; 0 otherwise).

4.4.4. Technological field

Though firms in our sample are all biotechnology firms, they compete in different niches within this industry. To account for sectoral differences, we included indicator variables representing participation in various segments of biotechnology. Following Stuart et al. (1999), we included four categorical variables to indicate whether the start-up firm operated in any of the four segments: *Genetic Engineering*, *Protein Engineering*, *Immunology* and *Diagnostics*.

Firm Age is the number of years from the date of incorporation. It is both a control variable and also an important moderator in this study.

4.4.5. Public company

A significant number of firms in our sample experienced an IPO during the observation period. Since a firm's valuation may be substantially different between public and private stages, we introduced a dynamic categorical variable indicating whether a start-up was public in a specific year (1 = public; 0 otherwise) to control for the effect of capital market access on firm valuation.

4.4.6. Total alliances

Firms differ in their propensity to partner with external organizations. We used the total number of alliances prior to year t as a proxy for this underlying propensity. Moreover, this variable controls for the effect of overall network size on firm valuation.

4.4.7. Equity alliances

Equity alliance is a special case of strategic alliance in that it indicates financial resources flowing between the participative organizations. As discussed earlier, inter-firm partnerships can be viewed as channels of information and financial resource flows. Since our network heterogeneity primarily focuses on optimizing information flow, it is necessary to parse out the potential effect of financial flows on valuation. We used the total number of equity alliances prior to year t as a proxy.

4.4.8. Valuation $t-1$

Firms are heterogeneous in terms of the numerous unobservable factors such as organizational culture, managerial skills or leadership. Exclusion of these important unobserved explanatory variables may substantially bias estimation (Greene, 2000). To control for these unobserved factors, in particular the serial correlation across years, entering the lagged dependent variable proves to be an acceptable solution (Jacobson, 1990).

4.5. Analysis

Our first analytic approach is to conduct panel regression on explanatory variables. Either fixed effects model or random effects model is appropriate depending the match between their strength and situational factors. We opted to use random effects model because: (a) the Hausman test revealed a non-significant difference between fixed effects and random effects model. In this situation, random effects model produces unbiased estimates that more efficient than fixed effect model does (Hausman, 1978); (b) to be consistent with previous studies, we included some time invariant variables such as geographic and segment dummies, which is only feasible in random effects model (Wooldridge, 2001). We created interaction terms between our theoretical variables and firm age. The sign and significance of those interaction terms will suggest the changes in impact of those variables on valuation.

The interaction approach, though straightforward, restricts the interaction relationship by either holding the slope constant or imposing a parametric functional form. To allow for more flexible interaction detection, we complement the results from the random effects model with a dynamic panel model, estimated by a regression technique called Minimum Distance Estimation (MDE). This dynamic panel model is an extension of the conventional fixed effects models with the benefits of controlling for heterogeneity and making unbiased and efficient estimates (Greene, 2000; Wooldridge, 2001). This dynamic panel model with MDE has a more flexible assumption on the relationship between error terms and explanatory variables. It allows us to have time-varying estimates of the parameters (β_t) instead of the time-invariant estimates of β and a parametric estimate of interaction term $\beta^* t$. Therefore, we are able to capture the relative change of effects without restricting them to be linear ex-ante. We also want to formally test whether this flexibility is supported by the data as compared to the conventional panel models. MDE provides a way

Table 1
Descriptive statistics and correlations.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 Firm valuation	3.47	2.16	1															
2 Market condition	3.69	.98	.35	1														
3 Biotech firm density	607.43	160.05	.53	.60	1													
4 CA area	.36	.48	.06	.02	.04	1												
5 MA area	.14	.35	.02	.00	.01	−.30	1											
6 Genetic engineering	.24	.43	.05	.02	.03	.04	−.00	1										
7 Protein engineering	.09	.29	.06	.02	.03	.05	−.01	−.10	1									
8 Immunology	.14	.34	−.06	−.01	−.02	−.05	.06	−.17	.04	1								
9 Diagnostics	.17	.38	−.04	.03	.03	−.10	−.02	−.01	.03	−.08	1							
10 Firm age	6.47	3.81	.59	.52	.73	−.05	−.02	−.02	−.03	.02	−.02	1						
11 Public dummy	.60	.49	.61	.44	.59	.02	−.00	.01	.05	−.01	−.02	.67	1					
12 Total alliances	8.42	9.54	.50	.36	.51	−.02	−.01	.07	−.01	−.09	−.01	.55	.48	1				
13 Equity alliances	.79	1.33	.39	.17	.28	.06	−.04	.03	.03	−.07	−.06	.33	.33	.54	1			
14 Valuation $t-1$	3.37	2.11	.80	.40	.55	.06	.02	.04	.06	−.04	−.04	.62	.63	.50	.39	1		
15 Innovative capability	3.67	6.71	.35	.13	.26	.09	−.02	.11	.07	−.09	.00	.24	.28	.36	.33	.32	1	
16 Network heterogeneity	.07	.07	.13	.03	.01	−.03	−.02	.02	.01	.04	.05	.04	.07	−.16	−.08	.02	−.06	1
17 Network status	.99	1.49	.35	.18	.26	−.05	−.02	.08	−.02	−.06	−.03	.26	.31	.60	.43	.33	.32	−.05

Total number of valid observations, $N = 1725$.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

to estimate structural form parameters that are a specific function of reduced form parameters and test which one is more adequate and is widely used in panel data analysis (Cameron and Trivedi, 2005; Chamberlain, 1984). The econometrics of the MDE is described in detail in Appendix B.

One potential methodological issue is sample selection bias. The sample firms with valuation records might be substantially different from those being excluded due to lack of valuation data. It is plausible that successful and bigger firms are more likely to be selected to our sample. We followed the conventional two stage procedure (Heckman, 1979). At the first stage, we used firm characteristics to predict the possibility of being selected and generate the inverse Mill's ratio (IMR). Then at the second stage, we entered *IMR* into the regression to control the selection bias.

5. Results

Table 1 reports the descriptive statistics and correlation matrix for the variables included. The panel regression of the innovative capability and inter-firm network's impact on valuation is reported in Table 2. We enter the control variables in model 1 (Table 2) and then the theoretical variables in a stepwise manner to test our hypotheses in subsequent models.

Table 2
Random effects GLS estimation of innovative capability and inter-firm network impact on valuation.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	Included	Included	Included	Included	Included	Included	Included
Inverse Mill's ratio	3.481**	3.133**	3.300**	3.135**	3.078**	3.101**	3.137**
	(.415)	(.414)	(.419)	(.415)	(.421)	(.414)	(.424)
Market condition	.124**	.123**	.126**	.123**	.122**	.128**	.125**
	(.028)	(.028)	(.028)	(.028)	(.028)	(.028)	(.028)
Biotech firm density/100	.044+	.025	.030	.025	.024	.032	.032
	(.023)	(.022)	(.023)	(.022)	(.022)	(.023)	(.022)
CA area	.648**	.593**	.618**	.593**	.586**	.590**	.605**
	(.085)	(.081)	(.082)	(.081)	(.081)	(.081)	(.082)
MA area	−.037	.004	−.014	.004	.009	−.001	−.004
	(.086)	(.079)	(.079)	(.079)	(.079)	(.079)	(.079)
Genetic engineering	.132*	.097+	.090	.098+	.098+	.093	.091
	(.064)	(.057)	(.058)	(.058)	(.057)	(.058)	(.057)
Protein engineering	.210*	.187*	.189*	.188*	.188*	.196*	.201*
	(.091)	(.083)	(.083)	(.083)	(.082)	(.083)	(.083)
Immunology	−.158*	−.157*	−.147*	−.156*	−.158*	−.155*	−.148*
	(.080)	(.072)	(.072)	(.072)	(.071)	(.072)	(.072)
Diagnostics	−.054	−.069	−.075	−.069	−.069	−.073	−.082
	(.071)	(.064)	(.065)	(.065)	(.064)	(.065)	(.064)
Firm age	−.056**	−.045**	−.057**	−.044**	−.042**	−.059**	−.049**
	(.011)	(.011)	(.012)	(.013)	(.012)	(.012)	(.015)
Public dummy	8.578**	7.687**	8.079**	7.693**	7.557**	7.609**	7.699**
	(.966)	(.965)	(.976)	(.967)	(.981)	(.964)	(.987)
Total alliances	.040**	.044**	.044**	.044**	.044**	.044**	.043**
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Equity alliances	.140**	.137**	.130**	.137**	.138**	.136**	.129**
	(.021)	(.020)	(.020)	(.020)	(.020)	(.020)	(.020)
Valuation $t-1$	.436**	.446**	.444**	.446**	.448**	.447**	.446**
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
Innovative capability		.013*	.017**	.013*	.012*	.013**	.017**
		(.005)	(.005)	(.005)	(.005)	(.005)	(.005)
Network heterogeneity		1.629**	1.701**	1.626**	1.608**	1.635**	1.657**
		(.356)	(.357)	(.359)	(.357)	(.356)	(.361)
Network status		.017	.023	.017	.014	.016	.013
		(.018)	(.019)	(.018)	(.019)	(.018)	(.019)
Innovative capability*Heterogeneity		.067	.029	.066	.077	.084	.052
		(.070)	(.071)	(.070)	(.071)	(.070)	(.074)
Innovative capability*Age			.002*				.003*
			(.001)				(.001)
Network heterogeneity*Age				.014			−.032
				(.109)			(.118)
Network status*Age					−.005+		−.011*
					(.003)		(.004)
Innovative capability*Heterogeneity*Age						.054**	.015
						(.019)	(.027)
Wald Chi-square	3376.661	3633.103	3648.942	3626.050	3646.952	3649.701	3675.342
R square	.681	.691	.693	.691	.692	.694	.703

$N=1725$ observations for 170 firms, ($^{\dagger}p<.1$, $^{*}p<.05$, $^{**}p<.01$, two tailed test.
Unstandardized coefficients are reported; standard errors in parentheses.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

Overall, the control variables exhibit a fairly strong impact on firm valuation and explain a significant portion of the variance (R-square = .68). The coefficients of IMR are positive and statistically significant ($p<.01$), suggesting that sample selection bias indeed is a relevant concern and justifying its inclusion (Wooldridge, 2001). The Market Condition is positively and significantly associated with firm valuation, indicating that firm valuation is influenced by the performance of the entire biotechnology industry.

We enter the theoretical variables in model 2 and their interaction terms with firm age in subsequent models. For example, we enter Innovative Capability * Firm Age in model 3 to test H1. In model 7, we enter all the variables to constitute a full model. Model 7 improves model fit over the baseline model significantly. With degree of freedom 4 and 1701, the corresponding F statistic is 17.18, substantively larger than the threshold 3.32 ($p<.01$). For models with interaction terms, interpretation of a variable's total effect will be decomposed into direct effect and interaction effect (Jaccard and Turrisi, 2003). Since the direct effects of our main theoretical variables remain stable across models, the sign and significance of the interaction terms can be used to interpret change in the total effect.

Our hypotheses address the *change in relative impact* of network and capability variables on firm valuation with increases in firm age. In models 3 and 7, the interaction term between innovative capability and firm age is positive and statistically significant (β = .002 and .003; $p<.05$). This result suggests that as a biotech start-up matures, its innovative capability measured by number of high-quality patents will have larger impact on firm valuation. Therefore, H1 is strongly supported.

The non-significant coefficients of network heterogeneity and firm age interaction in both models 4 and 7 indicate that the effect of network heterogeneity on valuation either does not change or does not show a consistent pattern with regard to aging. Consequently, hypothesis 2a is not supported.

The effect of network status on firm valuation declines with firm age. The coefficients of network status are negative in both models 5 and 7. In model 5, the effect is marginally significant ($\beta=-.005$, $p<.1$) but in model 7 it becomes significant ($\beta=-.011$, $p<.05$). Thus, our hypothesis 2b is supported.

Finally, we enter a three way interaction term to examine whether the complementary effect of innovative capability and network heterogeneity changes over time in a consistent manner (H3). In model 6, the coefficient of the three way interaction term is positive and significant (β = .054, $p<.01$). It remains positive but loses significance in the full model. Hence, hypothesis 3 is not supported if we choose model 7 as the benchmark. We further explore this result with the more sophisticated dynamic panel model described below.

The restrictive assumptions underlying the traditional interaction approach (requiring an monotonically increasing or decreasing functional form) as well as the generic panel models ($\beta_t=\beta$) may yield inaccurate estimates (Chamberlain, 1982). We attempt to remedy these restrictions with the dynamic panel model using MDE. First, we needed to ascertain whether partitioning the overall panel into stages is statistically appropriate. To do so, we conducted an overall test to examine the statistical difference between the dynamic panel and the generic panel model. The test statistic (similar to likelihood ratio test statistic) revealed significant different between the two specifications, rejecting the null hypothesis (Chamberlain, 1984).

In Table 3, we report the results of dynamic panel model using MDE. Due to the specification of our model and the computational power required, we can only allow for a balanced panel or equal length observation for each subject. To retain the maximum number of sample firms and the longest observation period, we had to truncate our sample to 152 firms with an observation period of seven years. We are particularly interested in the change of coefficients of the key variables. Essentially the results in Table 3 buttressed the results obtained from random effects GLS estimation. For example, the impact of innovative capability on firm valuation increases with firm age. We also found that the effect of network heterogeneity on firm valuation fluctuated with aging, confirming why the GLS estimation could not detect a significant interaction with conventional approach. To assist interpretation, we plotted the impact of innovative capability, network heterogeneity and their interaction in Figs. 1 and 2. In Fig. 1, we plot the relationship between innovative capability and valuation as moderated by firm age. In Fig. 2, we plot the standardized estimates from the MDE model (Table 3). We see that there is a positive and increasing coefficient for innovative capability and the complementary effect between network heterogeneity and innovative capability as a function of firm age. As

Table 3
Results of minimum distance estimation.

Predicators	Dependent variable: firm valuation						
	Age = 2	Age = 3	Age = 4	Age = 5	Age = 6	Age = 7	Age = 8
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Innovative capability	−.044+	−.005	.004	.003*	.011**	.023**	.057**
	(.026)	(.010)	(.006)	(.001)	(.003)	(.003)	(.003)
Network status	.035*	.021*	.001	0.003	−.028**	−.051**	−.055**
	(.016)	(.009)	(.017)	(.015)	(.013)	(.012)	(.012)
Network heterogeneity	2.943**	0.471*	2.701**	4.157**	2.803**	3.728**	3.086**
	(.221)	(.213)	(.196)	(.210)	(.218)	(.276)	(.308)
Innovative capability * Network heterogeneity	.033	.055	.157*	.138*	.231**	.483**	.526**
	(.164)	(.119)	(.073)	(.060)	(.059)	(.059)	(.037)

N = 152 firms, T = 7 years, 1064 valid observations.
+$p<.10$, *$p<.05$, **$p<.01$, two-tailed test.
Balanced panel, starts from age = 2 due to lagged valuation.

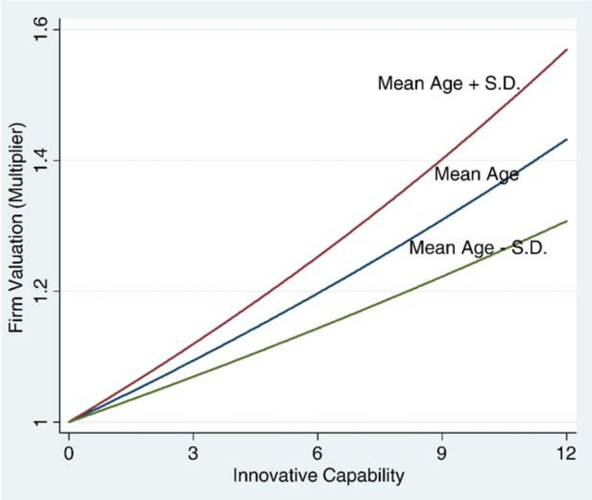

Fig. 1. Moderating effect of firm age on innovative capability and valuation.

predicted, network status has its highest impact on valuation in the early years but steadily decreases over time. Together, these findings raise some interesting theoretical and practical implications of a firm's networks and its capabilities as a function of its age.

5.1. Alternative explanations

Statistical results may be spurious if the hypothesized relationships are confounded with alternative explanations. In this study, besides generating multiple measures on each key variable, we also conducted additional analyses to rule out several major confounding arguments. First, because we use patents to derive our innovative capability measure, it is likely that we measure the propensity of the firm to patent rather than its ability to innovate. After all, unlike academic publications, patents are proprietary rights conferred to business firms that can be used as a strategic weapon either to protect their intellectual property or attack potential competitors (Hall and Ziedonis, 2001). To tease out this possibility, we collected information on patent claims which are a fairly good proxy of the coverage of a firm's proprietary knowledge and useful for protecting or attacking purposes (Lerner, 1994b). We found that this patent scope variable is almost orthogonal to patent citations and adding this new variable barely changes the results.

Though we controlled for valuation at $t-1$, we did not check if such a round was the first or subsequent round of financing. Therefore, we introduced controls for the financing round and the results are robust to this change. Further, age was negative and significant in our models (Table 2), which was puzzling because we expect that age to have a positive effect on valuation. We found that the coefficient for age turns negative when the lagged measure for valuation at $t-1$ is introduced. Our speculation is that the lag firm valuation variable may be correlated with firm age and hence captures the positive effect attributable to firm age. A common solution is to remove either variable from analyses. We experimented with removing the lag variable and found that our

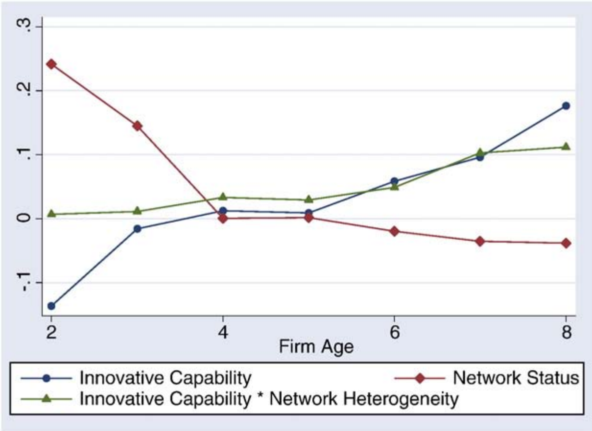

Fig. 2. Standardized estimates of factors impacting firm valuation.

results are not sensitive to the inclusion/exclusion of such variable. The hypothesized effects became even stronger without the lag variable. Nonetheless, lag firm valuation is an important control for autocorrelation and significantly improves model fit. So we decided to keep it as a control. Further, it is possible that the temporal pattern could be attributed to the specific time frame selected. To verify, we added calendar year dummies to our analyses. In addition, we conducted analyses with observations after firms became public to test whether our theory is sensitive to the transition from private to public status. Neither treatment materially changes our results.

6. Discussion and implications

In this study, we examine the relative temporal impact of innovative capability and inter-firm network on valuation of the start-up firm. While we find that both internally-developed resources (innovative capability) and external resources (network heterogeneity and network status) have a positive impact on firm value, these variables differ in their relative impact when start-ups grow older. We find that the positive effect of network status on valuation decreases with firm age. Concurrently, capabilities in the form of ability to generate new knowledge have an increasingly positive effect on valuation as start-ups become older. Our results provide critical insights into the changing impact of types of resources on value creation in entrepreneurial firms. The findings have significant implications for theories on organizational capabilities, networks, and wealth creation and are discussed next.

6.1. How and when do capabilities matter?

The literature on organizational capabilities has tended to focus on the successful deployment of a capability, i.e. executing a capability increases performance, but rarely considers the temporal consequences of the development of capabilities. In arguing for dynamic capabilities, Teece et al. (1997) note that the heterogeneity in firms' abilities to continually reconfigure routines and resources to meet evolving competitive conditions is the premise for sustained performance differences across firms. While there are some conceptual studies which argue that the timing of capability development has performance implications (e.g. Helfat and Peteraf, 2003), to our knowledge, this is the first empirical study to document a truly dynamic scenario of capabilities and its effects.

Our results confirm the positive effect of innovative capability on firm performance in technology start-ups, consistent with other studies (e.g., Baum et al., 2000; Rothaermel and Deeds, 2006). However, our interaction terms with age (Table 2) and the MDE results (Table 3) provide an interesting twist to the interpretation of existing literature. That is, the effect of the internal capability, innovative capability in this study, may initially detract from value creation but subsequently increases in its relative positive impact on value creation. This finding is consistent with theoretical arguments made by Sapienza et al. (2006) who argue that capability investments during internationalization of new ventures may initially decrease survival rates but subsequently enhance growth prospects. By allowing the slope to vary in our MDE model, we show that initially there could be a negative impact but this effect turns positive after a few years. Future studies could follow our approach to unravel the dynamism in value creation or performance as driven by investments in capabilities.

Results of this study also confirm arguments made by Cockburn et al. (2000). In a study of pharmaceutical firms, these authors found that successful firms were those that invested in building R&D capabilities long before any payoffs could be expected. Similarly, our study shows that the relative impact of innovative capability on valuation is negligible and then subsequently increases with firm age. George (2005) found that when an organization learns from the experience of deploying a core capability, it can parlay these benefits into the development of complementary capabilities, thereby increasing performance not just through experiential learning within a core capability but also through a multiplicative effect on complementary capabilities. This study's results suggest a similar explanation that capabilities gain traction over time and generate value with experience in deploying these capabilities.

6.2. The timing of inter-firm network formation

The findings of this study provide valuable information for the role of networks in high technology start-up firms. Network or alliance studies confirm the value of such ties for R&D, product development and financial performance among others. This study adds to this literature by suggesting that the value of such ties is greater at early stages of the firm's life cycle, findings that have managerial relevance as well. For example, though alliances provide a strong endorsement effect in the absence of any credible information of the start-up firm's capabilities, such endorsement effects prove to be more valuable earlier rather than later (Stuart et al., 1999).

Whereas our study considered the impact of the external network on firm value, it is possible that these alliances may have a significant payoff in other intermediate outcomes that do not necessarily enhance value directly. For example, alliances as sources of information and R&D could be positive for ongoing research projects (Hoang and Rothaermel, 2005), but these projects may not necessarily materialize to create value within the observation period that we consider. Our study provides some evidence for the declining value of firm level partnerships over time. We use two measures of network characteristics—heterogeneity and status—future research could explore the implications of a broader set of network variables. For instance, social capital theory suggests that network embeddedness, a rather macro level network construct, matters in terms of enhancing performance. Though we considered only inter-organizational relationships in this study, it would be useful for scholars to understand the temporal impact of social or personal networks on firm value or performance of entrepreneurial firms (Florin et al., 2003). It is possible that the value of social ties also varies over time or is contingent upon the presence of other internal organizational capabilities. The results of this study encourage researchers to consider the dynamic effects of other network variables on performance.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

Our study reveals an intriguing pattern regarding the dynamic impact of internal vs. external resources on firm performance. Though the direct impact of network variables such as network heterogeneity was unchanged over time, the complementary effect between network heterogeneity and innovative capability or leveraging the network's impact may increase over time. Therefore, this result suggests that though we may observe the increasingly important role of organizational networks (Powell et al., 1996), their relative importance tends to change with firm age. Our study encourages further studies into the underlying causal mechanisms and the dynamism in their impact in start-ups.

We do, however, find a strong and growing complementary effect between innovative capability and network heterogeneity on firm valuation. This result is consistent with our theoretical arguments that firm age represents routine development and information accumulation. The development of routines has an enabling effect or boosts the complementary effect. Investors can collect, analyze, and infer the track record of technology start-ups as they grow older; where the total effect reflects an increasing firm value. Thus our study contributes to the strategy literature by showing how firms create value by creating synergies between their innovative capability and inter-firm networks.

6.3. Wealth creation and entrepreneurship

A critical part of the theoretical discourse on wealth creation is the impact of resources in entrepreneurial firms. For example, entrepreneurship theories discuss the importance of bricolage, or the ability to combine resources, and bootstrapping, or the stretching of scarce resources, to sustain a start-up firm (Baker and Nelson, 2005). In motivating organizational scholars to consider research in this area, Hitt et al. (2001) suggest that entrepreneurship and strategy literatures need to be integrated to examine entrepreneurial strategies that create wealth. These authors noted that outcomes from creation (i.e. entrepreneurship) and exploiting current advantages while exploring new ones (i.e. strategic management) can lead to tangible wealth creation. Whereas accounting measures of performance are indeed important, it is the ultimate outcome of wealth creation for the entrepreneurial team that may serve to motivate entrepreneurial behavior and spawn other new ventures (Stuart and Sorenson, 2003), enhance investor support and confidence (Nicholson et al., 2005), or increase the likelihood of subsequent partnering behavior (Anand and Khanna, 2000).

By estimating the time-varying effects of network resources and capabilities on valuation, we add to our understanding of the dynamism of types of resources and their relative impact on wealth creation. While we measured firm valuation in this study, there is a direct linkage between firm valuation and wealth creation. In start-ups, we argue that the firm-level network serves as both an information conduit and as informational cue. Our findings indicate that, from a dynamic perspective, at least the status endorsement effect declines due to the reduced uncertainty about the entrepreneurial opportunity and the increased maturity of start-ups in terms of developing routines, rules and procedures. For managerial practice, we note that while both innovative capability and external networks matter in terms of boosting firm valuation, it is the *timing* of deploying these resources that is critical. Start-ups seeking to maximize valuation should be cognizant of the payoffs for attracting partners at different points in firm age.

7. Limitations and conclusion

Researchers need to exercise some caution when generalizing our results. First, our firms are drawn from a single industry. This sampling technique helps rule out certain methodological threats but restricts the ability to generalize the conclusions to a larger population. Nevertheless, we believe the general social processes underlying our study holds across settings that examine high technology firms. It is possible that much of the dynamic effect captured in our study is lost in non technology-intensive environments. The persistence (or absence) of time-varying effects across industry types would shed more light on the pacing of capability development or the temporal dynamics within start-up firms, areas that merit further investigation.

Another limitation is that our measure of innovative capability is crude. Future studies can employ a more fine-grained data (e.g. survey data, publication citation analysis) to gauge innovative capability. Our modeling technique enables us to measure with greater accuracy the dynamic effects of the independent variables. We achieve this goal at the expense of other aspects: the restrictions of the model exclude fixed variables, including geographic and technical field control variables because the dynamic panel model is fundamentally a fixed effects model. It is also computationally complex and time consuming due to the iterative computations involved. We encourage researchers to consider variations of this technique and possibly develop a simplified model that can also address the time-varying effects problem. Finally, our study leaves a few important questions unanswered. For example, we do not know what happens to the effects on firm valuation in the long run. Does the capability/network effect reach a plateau effect after increasing or declining when routine development and information accumulation reach their equilibrium stage when new routines or information contribute little to firm value? Or as Helfat and Peteraf (2003) suggested, do firm capabilities undergo a life cycle with periods of growth and decline? If this is the case and we extend our observation period long enough, it is possible that our conclusions on capability or network effects may change.

Limitations aside, our study makes critical contributions to the literature on the role of dynamic resources in firms. In this paper, by drawing from strategic and social frameworks, we offer a more complete response to the question: how do internal capability and external networks matter? Our study not only replicates the bulk of the literature on the direct effects of internal capabilities and network characteristics, but also more importantly, extends the literature by exploring the age related contingencies. We found that in our sample of biotechnology start-ups, the value of internal, innovative capabilities increased while the value of external network relationships decreased over time. We encourage future research to investigate the dynamism associated with organizational growth and the time-varying effect of different types of resources.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

Appendix A

Ranking of top pharmaceutical companies and medical schools.

Ranking	Pharmaceutical companies	Medical schools
1	Pfizer	Harvard
2	Glaxo Wellcome	Johns Hopkins
3	Merck	Duke
4	AstraZeneca	Yale University
5	Bristol–Myers Squibb	U of California at San Francisco
6	Aventis	Washington U, Mo.
7	Novartis	U of Pennsylvania
8	Johnson & Johnson	Columbia
9	Eli Lilly	Cornell
10	Roche	Stanford

To compute the ranking, we first gathered each year's ranking from Pharmaceutical Executive (1999–2005) and US news & world report (1990–1998). Then we average their ranking across years and sort the order again to generate a new ranking.

Appendix B. Minimum distance estimation

Section B.1. Minimum distance estimator of augmented panel data model

The model we consider is the following:

$$y_{it} = \beta_{t,0} + \beta_{t,1}x_{it,1} + \dots + \beta_{t,k-1}x_{it,k-1} + \gamma_t A_{it} + \delta_t c_{it} + \varepsilon_{it}, \forall i,t \tag{A.1}$$

Where c_{it} is the unobservable firm-specific effect, which is allowed to vary over time in our model:

$$c_{it} = \alpha_1 c_{i,t-1} + \alpha_2 A_{i,t-1} + \eta_t \quad \forall t > 1 \tag{A.2}$$

From Eqs. (A.1) and (A.2), we have:

$$\begin{aligned} y_{it} = {} & \beta_{t,0} - \frac{\delta_t\alpha_1}{\delta_{t-1}}\beta_{t-1,0} + \frac{\delta_t\alpha_1}{\delta_{t-1}}y_{i,t-1} + \beta_{t,1}x_{it,1} + \dots + \beta_{t,k-1}x_{it,k-1} + \gamma_t A_{it} \\ & - \frac{\delta_t\alpha_1}{\delta_{t-1}}\left(\beta_{t-1,1}x_{it-1,1} + \dots + \beta_{t-1,k-1}x_{it-1,k-1}\right) + \left(\delta_t\alpha_2 - \gamma_{t-1}\frac{\delta_t\alpha_1}{\delta_{t-1}}\right)A_{i,t-1} + \left(\varepsilon_{it} - \frac{\delta_t\alpha_1}{\delta_{t-1}}\varepsilon_{i,t-1} + \delta_t\eta_t\right) \end{aligned} \tag{A.3.1}$$

The unrestricted version of Eqs. (A.3.1) and (A.3.2) takes the form of

$$\begin{aligned} y_{it} = {} & \varphi_{t,1} + \varphi_{t,2}y_{i,t-1} + \varphi_{t,3}x_{it,1} + \dots + \varphi_{t,k+1}x_{it,k-1} + \varphi_{t,k+2}A_{it} \\ & + \varphi_{t,k+3}x_{it-1,1} + \dots + \varphi_{t,2k+1}x_{it-1,k-1} + \varphi_{t,2k+2}A_{i,t-1} + v_{it} \end{aligned} \tag{A.3.2}$$

Because the lagged dependent variable $y_{i,t-1}$ in Eqs. (A.3.1) and (A.3.2) is an explanatory variable and correlated with error term $\varepsilon_{i,t-1}$, an ordinary least squares (OLS) regression would be biased. Therefore, we resort to instrumental variable regression. Let's denote:

$$W_{it} = \left(1\ y_{i,t-1}\ x_{it,1}\ \dots\ x_{it,k-1}\ A_{it}\ x_{it-1,1}\ \dots\ x_{it-1,k-1}\ A_{it-1}\right) \tag{A.4}$$

Then we can rewrite Eq. (A.3.2) as

$$y_{it} = W_{it}\varphi_t + v_{it} \tag{A.5}$$

We choose our instrumental variable as

$$Z_{it} = \left(1\ x_{it,1}\ \dots\ x_{it,k-1}\ A_{it}\ x_{it-1,1}\ \dots\ x_{it-1,k-1}\ A_{it-1}\ x_{it-2,1}\ \dots\ x_{it-2,k-1}\ A_{it-2}\right) \tag{A.6}$$

Which automatically satisfies the criteria of instrumental variable choice:

$$E(Z'_{it}W_{it}) \neq 0 \quad \text{and} \quad E(Z_{it}v_{it}) = 0.$$

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

Stack up individual W_{it}'s, Z_{it}'s and y_{it}'s,

$$W_t = (W_{1t},\dots,W_{Nt})'$$
$$Z_t = (Z_{1t},\dots,Z_{Nt})'$$
$$y_t = (y_{1t},\dots,y_{Nt})'$$

We can get our two stage least squares (2SLS) estimator for φ_t for all $t \geq 3$:

$$\varphi_{t,2SLS} = \left[W'tZ_t(Z'tZ_t)^{-1}Z'tW_t\right]^{-1}W'tZ_t(Z'tZ_t)^{-1}Z'ty_t \tag{A.7}$$

Because our theoretical model (A.1)–(A.3.2) concerns about the connections of coefficients over time, the 2SLS estimator could not capture this dynamic structure. We proceed to derive three stage least squares (3SLS) estimator of all our coefficients.

To do that, first we need to obtain the 2SLS residuals for each period:

$$\hat{v}_{it} = y_{it} - W_{it}\varphi_{t,2SLS} \tag{A.8}$$

Define

$$\hat{v}_t = (\hat{v}_{1t},\dots,\hat{v}_{Nt})' \tag{A.9}$$

$$S_{ts} = \frac{1}{N}\hat{v}'t\,\hat{v}_s \tag{A.10}$$

Then the matrix of mean squares and cross products of 2SLS residuals S would have the t,sth element as S_{ts}.

Now define

$$vech(x_i) = \left(1\ x_{i1,1}\ \dots\ x_{i1,k-1}\ A_{i1}\ \dots\ x_{iT,1}\ \dots\ x_{iT,k-1}\ A_{iT}\right)' \tag{A.11}$$

$$X = \left(vech(x_1)'\ \dots\ vech(x_N)'\right)' \tag{A.12}$$

$$\bar{M} = X(X'X)^{-1}X' \tag{A.13}$$

$$W = \begin{pmatrix} W_3 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & W_T \end{pmatrix} \tag{A.14}$$

$$Y = (y_3\ \dots\ y_T)' \tag{A.15}$$

Then

$$\Phi_{3SLS} = \left[W'\left(S^{-1}\otimes\bar{M}\right)W\right]^{-1}W'\left(S^{-1}\otimes\bar{M}\right)Y \tag{A.16}$$

Where $\Phi_{3SLS} = (\phi_3 \dots \phi_T)'$ and ϕ_t is the 3SLS counterpart of $\varphi_{t,2SLS}$.

So far, the 3SLS estimator takes into consideration the dynamic structure of coefficients, but what we are interested in is not Eq. (A.3.2). Indeed, our ultimate goal is to recover the parameters in Eq. (A.3.1), or the βs, γs and δs. To do that, we need to conduct the minimum distance estimation technique because apparently non-linear combinations of βs, γs and δs constitute the counterparts of our 3SLS estimator in Eq. (A.3.1). The essence of this technique is to create a distance metric between model parameters and their sample analogs. This technique is similar to the traditional OLS in the sense that the distance measure OLS utilizes is the distance between true and estimated values and the parameters, which minimize the sum of squared distances.

Formally, denote

$$\theta = \left(\beta_{2,1}\ \dots\ \beta_{T,1}\ \dots\ \beta_{2,k-1}\ \dots\ \beta_{T,k-1}\ \gamma_2\ \dots\ \gamma_T\ \delta_3\ \dots\ \delta_T\ \alpha_1\ \alpha_2\right)' \tag{A.17}$$

Parameters start from the second period because the lagged dependent variable is included, so $t = 1$ is treated as the initial period. δs start from the third period because δ_2 is set to 1.

Then $f(\theta) = [f(\theta)_3 \dots f(\theta)_T]'$ is the Eq. (A.3.1) counterpart of Φ_{3SLS}, excluding all intercepts. To be more specific, $f(\theta)$ is the Eq. (A.3.1) version parameter estimate, and $\Phi_{3SLS,\text{no intercept}} = [(0\ I_{2k+1})\otimes I_{T-2}]\Phi_{3SLS}$ is the Eq. (A.3.2) version parameter estimate. The reason we use $f(\theta)$ is natural, since from Eq. (A.3.1), we can see coefficients for explanatory variables are actually non-linear functions of fundamental parameters in θ.

Denote

$$\hat{\Lambda}_{\text{no intercept}} = \left[\begin{pmatrix}0 & I_{2k+1}\end{pmatrix} \otimes I_{T-2}\right]\left[W'\left(S^{-1} \otimes \bar{M}\right)W\right]^{-1}\left[\begin{pmatrix}0 & I_{2k+1}\end{pmatrix} \otimes I_{T-2}\right]' \tag{A.18}$$

We have our minimum distance estimator of θ:

$$\hat{\theta}_{min \text{ dis}} = \arg\min_{\theta}\left[\Phi_{\text{3SLS,no intercept}} - f(\theta)\right]' \hat{\Lambda}^{-1}_{\text{no intercept}} \left[\Phi_{\text{3SLS,no intercept}} - f(\theta)\right] \tag{A.19}$$

Section B.2. Test of augmented panel data model vs. traditional panel data model

The above model is called augmented panel data model because it differs from traditional panel data model in the essence that we allow for time-varying coefficients. A natural question could be raised: is it necessary to create time-varying coefficients? Or maybe time-fixed coefficients could do a decent job? To analyze this, we create two competing hypotheses:

H0. Effects of explanatory variables are time-fixed.

H1. Effects of explanatory variables are time-varying.

If H0 is true, our model becomes

$$y_{it} = \beta_0 + \beta_1 x_{it,1} + \ldots + \beta_{k-1} x_{it,k-1} + \gamma A_{it} + c_{it} + \varepsilon_{it}, \forall i, t \tag{A.20}$$

Which leads to:

$$y_{it} = y_{i,t-1} + \beta_1\left(x_{it,1} - x_{it-1,1}\right) + \ldots + \beta_{k-1}\left(x_{it,k-1} - x_{it-1,k-1}\right) + \gamma\left(A_{it} - A_{i,t-1}\right) + \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right) \tag{A.21}$$

Now

$$\theta_{\text{fixed}} = \left(\beta_1 \;\ldots\; \beta_{k-1} \gamma\right)' \tag{A.22}$$

The minimum distance estimator for θ_{fixed} solves

$$\min_{\theta}\left[\Phi_{\text{3SLS,no intercept}} - f(\theta_{\text{fixed}})\right]' \hat{\Lambda}^{-1}_{\text{no intercept}} \left[\Phi_{\text{3SLS,no intercept}} - f(\theta_{\text{fixed}})\right] \tag{A.23}$$

Denote

$$d_1 = \left[\Phi_{\text{3SLS,no intercept}} - f\left(\hat{\theta}_{min \text{ dis}}\right)\right]' \hat{\Lambda}^{-1}_{\text{no intercept}} \left[\Phi_{\text{3SLS,no intercept}} - f\left(\hat{\theta}_{min \text{ dis}}\right)\right] \tag{A.24}$$

$$d_2 = \left[\Phi_{\text{3SLS,no intercept}} - f\left(\hat{\theta}_{\text{fixed}}\right)\right]' \hat{\Lambda}^{-1}_{\text{no intercept}} \left[\Phi_{\text{3SLS,no intercept}} - f\left(\hat{\theta}_{\text{fixed}}\right)\right] \tag{A.25}$$

It has been proved (Chamberlain, 1982, 1984) that, under the null H0,

$$d_2 - d_1 \xrightarrow{d} \chi^2_{(T-2)k+T} \tag{A.26}$$

So, if the statistic $d_2 - d_1$ is larger than the critical value $\chi^2_{\alpha,(T-2)k+T}$, $H0$ is rejected.

Section B.3. Single parameter test

To do this, we need to find variance of θ by the usage of δ-method.
If $F = \partial f(\theta)/\partial\theta'$,
then $\Delta = \text{var}(\hat{\theta}_{\text{min dis}}) = [F'\hat{\Lambda}^{-1}_{\text{no intercept}} F]^{-1}$.
It's been proved (Chamberlain, 1982, 1984) that

$$\hat{\theta}_{min \text{ dis}} - \theta_0 \xrightarrow{d} N(0, \Delta) \tag{A.27}$$

Hence, to test whether any parameter is significantly different from 0, our test statistic would be $\frac{\hat{\theta}_j}{\sqrt{var(\hat{\theta}_j)}}$, which is asymptotically normal (0,1) under the null H0: $\theta_j = 0$.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

References

Ahuja, G., Katila, R., 2001. Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. Strategic Management Journal 22 (3), 197–220.

Alvarez, S.A., 2001. How entrepreneurial firms can benefit from alliances with large partners. Academy of Management Executive 15 (1), 139–148.

Anand, B.N., Khanna, T., 2000. Do firms learn to create value? The case of alliances. Strategic Management Journal 21 (3), 295–315.

Baker, T., Nelson, R.E., 2005. Creating something from nothing: resource construction through entrepreneurial bricolage. Administrative Science Quarterly 50 (3), 329–366.

Baum, J.A.C., Calabrese, T., Silverman, B.S., 2000. Don't go it alone: alliance network composition and startups' performance in Canadian biotechnology. Strategic Management Journal 21 (3), 267–294.

Binder, G., Bashe, P., 2008. Science Lessons: What the Business of Biotech Taught Me About Management. Harvard Business School Press.

Bogdan, B., Villiger, R., 2008. Valuation in Life Sciences: A Practical Guide. Springer.

Borgatti, S.P., Everett, M.G., Freeman, L.C., 2002. Ucinet for Windows: Software for Social Network Analysis. Analytic Technologies, Harvard, MA.

Burrill, G.S., 1992. Biotech 93: Accelerating Commercialization: An Industry Annual Report. Ernst & Young, San Francisco, CA.

Burt, R.S., 1992. Structural Holes: The Social Structure of Competition. Harvard University Press, Cambridge, MA.

Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge University Press, New York.

Carter, R., Manaster, S., 1990. Initial public offerings and underwriter reputation. Journal of Finance 45, 1045–1068.

Chamberlain, G., 1982. Multivariate regression models for panel data. Journal of Econometrics 18 (1), 5–46.

Chamberlain, G., 1984. Panel data. In: Griliches, Z., Intriligator, M. (Eds.), Handbook of Econometrics, vol. 2. North-Holland, Amsterdam, pp. 1247–1318.

Chang, S.J., 2004. Venture capital financing, strategic alliances, and the initial public offerings of Internet startups. Journal of Business Venturing 19 (5), 721–741.

Cockburn, I.M., Henderson, R.M., Stern, S., 2000. Untangling the origins of competitive advantage. Strategic Management Journal 21 (10–11), 1123–1145.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Administrative Science Quarterly 35 (1), 128–152.

DeCarolis, D.M., Deeds, D.L., 1999. The impact of stocks and flows of organizational knowledge on firm performance: an empirical investigation of the biotechnology industry. Strategic Management Journal 20 (10), 953–968.

Deeds, D.L., Decarolis, D., 1997. The impact of firm-specific capabilities on the amount of capital raised in an initial public offering: evidence from the biotechnology industry. Journal of Business Venturing 12 (1), 31–46.

Florin, J., Lubatkin, M., Schulze, W., 2003. A social capital model of high-growth ventures. Academy of Management Journal 46 (3), 374–384.

Freeman, J.H., Carroll, G.R., Hannan, M.T., 1983. The liability of newness: age dependence in organizational death rates. American Sociological Review 48 (5), 692–710.

George, G., 2005. Learning to be capable: patenting and licensing at the Wisconsin Alumni Research Foundation 1925–2002. Industrial and Corporate Change 14 (1), 119–151.

George, G., Zahra, A., Wood, D., 2002. The effects of business-university alliances on innovative output and financial performance: a study of publicly traded biotechnology companies. Journal of Business Venturing 17 (6), 577–609.

Greene, W.H., 2000. Econometric Analysis, (4th ed.). Macmillan, New York.

Gulati, R., 1998. Alliances and networks. Strategic Management Journal 19, 293–317.

Hagedoorn, J., Cloodt, M., 2003. Measuring innovative performance: is there an advantage in using multiple indicators? Research Policy 32 (8), 1365–1379.

Hall, B.H., Ziedonis, R.H., 2001. The patent paradox revisited: an empirical study of patenting in the US semiconductor industry, 1979–1995. RAND Journal of Economics 32 (1), 101–128.

Hand, J.R.M., 2007. Determinants of the round-to-round returns to pre-IPO venture capital investments in US biotechnology companies. Journal of Business Venturing 22 (1), 1–28.

Hannan, M.T., Freeman, J.H., 1977. The population ecology of organizations. American Journal of Sociology 82 (5), 929–964.

Hausman, J.A., 1978. Specification tests in econometrics. Econometrica 46 (6), 1251–1271.

Heckman, J.J., 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161.

Helfat, C.E., Lieberman, M.B., 2002. The birth of capabilities: market entry and the importance of pre-history. Industrial and Corporate Change 11 (4), 725–760.

Helfat, C.E., Peteraf, M.A., 2003. The dynamic resource-based view: capability lifecycles. Strategic Management Journal 24 (10), 997–1010.

Hitt, M.A., Ireland, R.D., Camp, S.M., Sexton, D.L., 2001. Strategic entrepreneurship: entrepreneurial strategies for wealth creation. Strategic Management Journal 22 (6–7), 479–491.

Hoang, H., Rothaermel, F.T., 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. Academy of Management Journal 48 (2), 332–345.

Jaccard, J., Turrisi, R., 2003. Interaction Effects in Multiple Regression, (2nd ed.). Sage Publications, Thousand Oaks, CA.

Jacobson, R., 1990. Unobservable effects and business performance. Marketing Science 9 (1), 74–85.

Janney, J.J., Folta, T.B., 2003. Signaling through private equity placements and its impact on the valuation of biotechnology firms. Journal of Business Venturing 18 (3), 361–380.

Kale, P., Dyer, J.H., Singh, H., 2002. Alliance capability, stock market response, and long term alliance success: the role of the alliance function. Strategic Management Journal 23 (8), 747–767.

Klepper, S., 2001. Employee startups in high-tech industries. Industrial and Corporate Change 10 (3), 639–674.

Lavie, D., 2006. The competitive advantage of interconnected firms: an extension of the resource-based view. Academy of Management Review 31 (3), 638–658.

Lavie, D., 2007. Alliance portfolios and firm performance: a study of value creation and appropriation in the US software industry. Strategic Management Journal 28 (12), 1187–1212.

Lee, C., Lee, K., Pennings, J.M., 2001. Internal capabilities, external networks, and performance: a study on technology-based ventures. Strategic Management Journal 22 (6–7), 615–640.

Lerner, J., 1994a. Venture capitalists and the decision to go public. Journal of Financial Economics 35 (3), 293–316.

Lerner, J., 1994b. The importance of patent scope: an empirical analysis. RAND Journal of Economics 25 (2), 319–333.

Levitt, B., March, J.G., 1988. Organizational learning. Annual Review of Sociology 14, 319–340.

Mowery, D.C., Sampat, B.N., Ziedonis, A.A., 2002. Learning to patent: institutional experience, learning, and the characteristics of U.S. university patents after the Bayh–Dole act, 1981–1992. Management Science 48 (1), 73–89.

Nicholson, S., Danzon, P.M., McCullough, J., 2005. Biotech-pharmaceutical alliances as a signal of asset and firm quality. Journal of Business 78 (4), 1433–1464.

Podolny, J.M., 2001. Networks as the pipes and prisms of the market. American Journal of Sociology 107 (1), 33–60.

Podolny, J.M., Stuart, T.E., Hannan, M.T., 1996. Networks, knowledge, and niches: competition in the worldwide semiconductor industry, 1984–1991. American Journal of Sociology 102 (3), 659–689.

Powell, W.W., Koput, K.W., Smith-Doerr, L., 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. Administrative Science Quarterly 41 (1), 116–145.

Powell, W.W., Koput, K.W., Smith-Doerr, L., Owen-Smith, J., 1999. Network position and firm performance: organizational returns to collaboration in the biotechnology industry. In: Andrews, S., Knoke, D. (Eds.), Networks In and Around Organizations, vol. 16. JAI Press, Greenwich, CT, pp. 129–159.

Rond, M.D., 2003. Strategic Alliances as Social Facts: Business, Biotechnology, and Intellectual History. Cambridge University Press.

Rothaermel, F.T., Deeds, D.L., 2006. Alliance type, alliance experience and alliance management capability in high-technology ventures. Journal of Business Venturing 21, 429–460.

Sanders, W.G., Boivie, S., 2004. Sorting things out: valuation of new firms in uncertain markets. Strategic Management Journal 25 (2), 167–186.

Sapienza, H.J., Autio, E., George, G., Zahra, S.A., 2006. A capabilities perspective on the effects of early internationalization on firm survival and growth. Academy of Management Review 31 (4), 914–933.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001

Shan, W., Walker, G., Kogut, B., 1994. Interfirm cooperation and startup innovation in the biotechnology industry. Strategic Management Journal 15 (5), 387–394.
Sorensen, J.B., Stuart, T.E., 2000. Aging, obsolescence, and organizational innovation. Administrative Science Quarterly 45 (1), 81–112.
Stinchcombe, A.L., 1965. Social structure and organizations. In: March, J.G. (Ed.), Handbook of Organizations. Rand McNally, Chicago, IL.
Stuart, T.E., Sorenson, O., 2003. Liquidity events and the geographic distribution of entrepreneurial activity. Administrative Science Quarterly 48 (2), 175–201.
Stuart, T.E., Hoang, H., Hybels, R.C., 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. Administrative Science Quarterly 44 (2), 315–349.
Teece, D.J., Pisano, G.P., Shuen, A., 1997. Dynamic capabilities and strategic management. Strategic Management Journal 18 (7), 509–533.
Wooldridge, J.M., 2001. Econometric Analysis of Cross Section and Panel Data. MIT Press, Boston, MA.
Zaheer, A., Bell, G., 2005. Benefiting from network position: firm capabilities, structural holes, and performance. Strategic Management Journal 26 (8), 809–825.
Zahra, S.A., George, G., 2002. Absorptive capacity: a review reconceptualization and extension. Academy of Management Review 27 (2), 185–203.

Please cite this article as: Zheng, Y., et al., The dynamic impact of innovative capability and inter-firm network on firm valuation: A longitudinal study of biotechnology ..., Journal of Business Venturing (2009), doi:10.1016/j.jbusvent.2009.02.001