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MANAGING LIQUIDITY IN RESEARCH-INTENSIVE FIRMS: SIGNALING AND CASH FLOW EFFECTS OF PATENTS AND ALLIANCE ACTIVITIES

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The effective holding and management of liquid assets is critical to success in research-intensive industries. The primary output of invention is new knowledge. However, because of its 'sticky' characteristics, knowledge may not easily diffuse to external shareholders, leading to knowledge asymmetries between managers/employees and external suppliers of capital. Many valuable R&D projects may thus fail to attract external financing, limiting a firm's ability to invest in R&D. In this study, we examine how the cash flow and signaling properties of a firm's patents and certain aspects of its alliance strategy can attenuate such problems. Specifically, we suggest that a firm's R&D investments positively predict the level of its liquid asset holdings. This is due to the fact that invention-induced knowledge asymmetries increase the firm's cost of accessing external liquid capital. However, holding cash entails opportunity costs. In this regard, we also find that patent production and certain alliance activities provide important signaling mechanisms, which reduce knowledge asymmetries between the firm and capital markets, and consequently lower the firm's need to hold liquid assets. Empirical tests were conducted using a sample of 108 U.S-based biotechnology firms. Copyright © 2009 John Wiley & Sons, Ltd.

INTRODUCTION

A considerable volume of research has noted the problems associated with financing research and development (R&D) activities (see Hall, 2005 for a review). Indeed, it is now widely accepted that investing in R&D affects a firm's inventive success and may significantly impact organizational performance (Helfat, 1994). However, invention may also precipitate knowledge asymmetries between employees/managers and external parties such as providers of capital (Anton and Yao, 2004), leading to a reluctance by these parties to finance R&D at a reasonable cost. The primary output of invention is new knowledge (Arrow, 1962). Knowledge, though, may not easily diffuse to external shareholders due to its 'tacitness' or other 'sticky' characteristics (Hall, 2000; von Hippel, 1994), or because of attempts by managers to forestall imitation by competitors (Bhattacharya and Ritter, 1983). Many valuable R&D projects may thus fail to attract external financing, leading to their abandonment by the firm (Leland and Pyle, 1977; Myers and Majluf, 1984). In this study, we examine how the cash flow and signaling properties of a firm's patents and certain aspects of its alliance strategy can attenuate such problems.

Studies indicate that R&D-active firms tend to rely relatively heavily on internally held cash (that held in reserve as financial slack or 'liquidity') to fund R&D, thereby reducing these costs (Hall, 2005; Kim, Mauer, and Sherman, 1998;

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Opler *et al*., 1999; Papaioannou, Strock, and Travlos, 1992).[1] This in no way suggests that high R&D firms do not rely on external financing, only that certain amounts of cash are held in reserve to fund needs as they emerge. This provides a simple solution to the financing problem were it not for the costs that holding cash imposes. Cash generally returns considerably less than the firm's cost of capital. Furthermore, the need to *hold* cash may conflict with the strategic desire to *invest* it in R&D. The R&D-intensive firm therefore, faces a tradeoff between funding current projects and stockpiling cash for future projects.

We describe remedies for this tradeoff by examining how a firm's patenting and alliance activities alter the level of cash the firm needs to set aside for future projects. Consistent with previous work, we believe that research-active firms will finance some R&D activities by internally held cash (Kim *et al*., 1998; Opler *et al*., 1999; Papaioannou *et al*., 1992). Research activities provide the firm with the ability to develop new knowledge, leading to potential knowledge asymmetries between the firm and external parties. Holding relatively high levels of liquid assets allows the firm to reduce the costs of raising external funds on an 'as needed' basis. However, we argue that patent production provides the ability to generate cash through avenues such as product or licensing revenues, and also by providing tangible signals about the firm's ability to transform research investments into new and potentially valuable knowledge. Patent signals should, therefore, increase external investors' valuations of the firm, making external capital more accessible, and concomitantly lowering the need to hold liquid assets. We also predict that patents will negatively moderate the relationship between a firm's R&D and its need to hold liquid assets since patents signal successful outcomes of the otherwise intangible R&D process.

Similarly, exploitation alliances or those alliances focused on subtle refinement of existing technologies and products (e.g., Rothaermel, 2001) should also reduce a firm's need to hold cash. Alliances of this sort generally couple one firm's technology with the complementary assets (e.g., distribution, manufacturing) of a partner to incrementally extend the scope of an existing technology (Koza and Lewin, 1998). Such alliances can be relatively quick to produce new inventions (Gupta, Smith, and Shalley, 2006) and thus increase the likelihood of near term cash flows. We contrast this with exploration alliances, which focus on the creation of fundamentally new technologies. Since they often involve R&D collaboratory arrangements, exploration alliances will increase the likelihood of knowledge production (e.g., Dyer and Hatch, 2006; Kale and Singh, 2007; Kale, Singh, and Perlmutter, 2000), and therefore, may lead to greater knowledge asymmetries. Hence, we predict that exploration alliances will increase an R&D-intensive firm's need to hold liquid capital. Empirical tests using a sample of 180 U.S.-based biotechnology firms confirm our hypotheses.

THEORY AND HYPOTHESES

Invention entails the recombining of knowledge and resources in novel and potentially valuable manners (Schumpeter, 1934). Because invention entails the search for new ideas in currently obscured domains, the process is fraught with risk (Freeman, 1982; Mansfield, 1968). Liquid assets refer to cash and equivalents that are fluidly exchanged in various markets. Theoretically, if external markets operate efficiently, firms would not need to concern themselves with liquidity management. Legitimate needs for cash would be serviced (at commensurate costs) through capital markets (Kim *et al*., 1998). Firms' holding of excess cash could actually reduce shareholder wealth because slack resources, by definition, are not immediately invested in operations, and thus do not earn returns which meet (or exceed) the firm's cost of capital.

Furthermore, Jensen (1986) has noted agency costs associated with holding excess cash. Managers, who may not enjoy the degree of rights to a firm's profits that (other) shareholders do, can act to maximize personal utilities instead of firm profits. This possibility, coupled with shareholders distance from firm operations, provides an impetus for managerial opportunism.

However, access to cash allows patience as technological advances may be especially resource draining and time consuming. Easy access to cash is critical in the presence of numerous delays inherent in experimental trials, regulatory requirements, and failed inventive efforts, which drain

[1] We will use 'cash held in reserve' and 'liquid assets' interchangeably throughout the rest of this article.

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the firm of cash needed for successful invention. Slack resources, in other words, allow experimentation with new resource combinations that, if ultimately worthless, minimize the vulnerability of other operations to resource shortage (e.g., Cyert and March, 1963).

Cash obtained from external capital markets can also fund these activities, but not without considerable costs. Use of external capital markets entails administrative costs (e.g., paying investment bankers) and delays (e.g., from regulatory filings). Furthermore, external investors may not be able to evaluate the firm's inventive efforts. Much of what governs successful invention is organizational tacit knowledge that establishes implicit rules of activity and conduct (e.g., Henderson and Cockburn, 1994; Kogut and Zander, 1992). Knowledge complexity and the intertwined nature of technologies embodied in it (e.g., knowledge of inorganic, organic and biochemistries), possession of supporting skills (e.g., facility with statistical techniques), and so forth make knowledge 'sticky' as well (von Hippel, 1994). Even when the R&D process does provide a codified set of technologies, ease of knowledge diffusion may allow imitation by competitors, decreasing the value of external capital (Bhattacharya and Ritter, 1983).

Such problems make shareholders' abilities to differentiate among managerial competence, self-interest, and the effects of environmental conditions especially difficult in firms pursuing invention. For firms seeking external financing, a 'lemons' problem (Akerlof, 1970) can result where investors cannot easily distinguish between high- and low-quality firms (see also Stulz, 1990). In such cases capital markets will value a high-quality firm at no more than the market value of the average firm, raising the cost of capital for the high-quality firm, and pressuring it to forego profitable investment (Leland and Pyle, 1977; Myers and Majluf, 1984). Consistently, empirical studies have found a tendency for research-intensive firms to hold relatively high amounts of liquid capital to offset this 'underinvestment' problem (Kim *et al*., 1998; Opler *et al*., 1999; Papaioannou *et al*., 1992).

Liquidity and patents

Holding cash may partly remedy the 'underinvestment' problem, but this strategy is not costless. As noted, the holding of cash yields low returns that may prompt agency costs (e.g., Jensen, 1986). Maintaining cash creates a further tradeoff between the need to *hold* cash for future projects and the opportunity to profitably *invest* it in current R&D. In addition to empirical findings suggesting that high-R&D firms need to stockpile cash (i.e., R&D $\rightarrow$ liquidity), other studies (Hao and Jaffe, 1993; Himmelberg and Petersen, 1994; Scellato, 2007) find that high-R&D firms, because of the high cost of external finance, rely on internally held funds to support R&D (i.e., liquidity $\rightarrow$ R&D). In aggregate, high-R&D firms stockpile cash for future projects (i.e., R&D $\rightarrow$ liquidity), and once they identify future projects, these firms will fund the projects with the stockpiled cash (i.e., liquidity $\rightarrow$ R&D).

The firm could easily manage this relationship if it knew of all potential R&D projects/needs simultaneously and upfront. The firm could simply pick those that were most profitable and for which they had enough cash in reserve. However, the firm rarely has this opportunity since new projects often emerge in sequential fashion. Frequently, the firm will have to choose projects presented in one period without knowing if any (more) profitable projects will emerge in subsequent periods (e.g., it may be unable to pursue a potentially valuable product opportunity at time t_2 because of the resources it devoted to a less valuable project at t_1). Ultimately, the R&D-intensive firm in these circumstances faces a tradeoff between funding or maintaining current projects, or stockpiling cash for future projects. Furthermore, since learning from R&D in earlier periods often provides knowledge on which to base future R&D (Roberts and Weitzman, 1981), forgoing early projects may decrease the value of later projects.

How then, can R&D-intensive firms reduce the costs associated with accessing external capital markets, and thus reduce the need to hold (and cost of) liquid assets? Indeed, it would seem that a firm would prefer to access external capital at reasonable costs, thereby minimizing the costs of holding idle liquid assets. We suggest that one way a firm can accomplish this is via the cash flow potential and signaling attributes of its patent portfolio.

Patenting can signal the value or effectiveness of a firm's R&D program to capital markets, informing outsiders of the inventive abilities of the firm and reducing asymmetries and attendant costs of

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external capital procurement. Although not indicating the development of a marketable product or process, patents do demonstrate 1) the ability to pursue knowledge recombination; 2) the possession of potentially useful or valuable technology; and 3) the ability to go beyond basic understandings to produce technology that is not 'obvious to a person having ordinary skill in the pertinent art' (Barrett, 1996: 32; Stephan, 1996). Patents provide robust signals of the effectiveness of a firm's inventive efforts as they represent tangible outputs of the invention process (Griliches, 1990). Patenting can also confer a significant amount of prestige upon a firm's scientists. Rewards of this type, in turn, can lead to more enthusiastic and cost-effective research. It can also confer greater prestige on the firm as a whole, resulting in the receipt of more government research grants (e.g., Stephan, 1996) or the ability to attract more capable alliance partners (e.g., Larson, 1992). Patenting can also reduce hiring costs by providing external signals to labor markets about the firm's technological ability.

Potential imitators, furthermore, cannot easily duplicate such signals, as patents are neither easily granted nor inexpensive to pursue. Patents are only granted on novel technology, and (at least in the United States) to the first individual or group that can demonstrate rightful legal claims over the technology. Patenting, therefore, tends to provide clear distinctions between those that can successfully advance through the invention process and those that cannot. Moreover, as patent filings are publicly available, information contained in these filings can be used by external capital providers to assess the investment value of the firm (e.g., Hall, Jaffe, and Trajtenberg, 2005). In this manner, patents, at least in certain technological realms, mitigate problems noted by Bhattacharya and Ritter (1983) where firms seeking external finance can signal only in ways that reveal information to competitors. Since, from a legal standpoint, patents allow the owner to exclude others from the use of the underlying technology, and technologies are codified in the patent filing, patents provide a very effective vehicle with which to signal technological competence.

Patents also provide the owners with multiple options to derive more immediate cash flows (Chi and Levitas, 2007). A firm can, for example, choose to commercialize the technology underlying a patent, to license or to sell that technology. We should also note that patents vary in terms of their economic value (Trajtenberg, 1990). Certain patents may have little positive affect on a firm's fortunes. Production of *important* patents, however, has been shown to increase the stature of patenting companies within their respective scientific communities (Podolny, Stuart, and Hannan, 1996) since a firm's 'technical' capital (i.e., a firm's ability to produce new technologies, products, and/or processes) will be signaled by its patents (Ahuja, 2000). Thus, while a firm's simple count of patents may not necessarily reduce knowledge asymmetries since these simple counts may be noisy measures of firm capabilities (DeCarolis and Deeds, 1999), production of important patents in research intensive industries (e.g., biotechnology) may indeed reduce knowledge asymmetries between insiders and uninformed investors about the ability of the firm to transform investments in R&D into productive technologies (Heeley, Matusik, and Jain, 2007).

As such, we expect that the firm's accumulated success in patenting will provide a positive signal to external parties. Patents, weighted by their value, (hereafter 'patent value') should indicate a firm's inventive prowess, and should reduce capital costs as they inform external investors' about the abilities of the firm to successfully engage in the invention process, as well as the likelihood of achieving cash flows from the technology. The level of patent value, therefore, should negatively predict the level of liquid assets held by the firm.

Hypothesis 1: There is a negative relationship between a firm's patenting activity and its need to hold liquid assets such that the higher a firm's patent value, the lower will be its need to hold liquid assets.

Furthermore, we propose that because patenting activity will provide tangible outcomes of the otherwise intangible technology development process, patenting activity will lessen the knowledge asymmetry specific to R&D investment. The result will be that firms that allocate dollars toward R&D will hold less liquid assets if they patent as well. Put differently, we would expect the level of patent value to (negatively) moderate the relationship between the firm's level of liquidity and its R&D intensity.

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Hypothesis 2: A firm's patent value negatively moderates the relationship between a firm's investment in R&D and its need to hold liquid assets.

Liquidity and exploration and exploitation alliances

We expect alliance activity, both exploration and exploitation, to also impact the firm's need to hold liquid assets. Collaboration among firms in technology-intensive industries is now commonplace. Since no single firm by itself is a repository of all knowledge relevant to its own operations, collaborating to share knowledge is a key to success in many technology-intensive industries. Via collaboration, firms can pool their resources and technologies in ways that magnify their ability to engage in recombination/invention, and thus, accelerate their developmental processes (e.g., Ahuja, 2000). Furthermore, invention-induced knowledge asymmetries have been shown to increase the firms' reliance on alliance activities as a source of financing for R&D activities (Lerner, Shane, and Tsai, 2003; Gulati and Higgins, 2003).

Alliances, however, are not homogenous in terms of intended goals. In this study, we employ the exploitation/exploration dichotomy to differentiate between types of alliances (Rothaermel, 2001). Exploitation alliances focus partners' efforts on deepening existing knowledge by improving established designs, products, and services to meet the needs of existing customers and markets (Koza and Lewin, 1998; Rothaermel, 2001). Such alliances entail 'refinement, choice, production, efficiency, selection, implementation, execution' (March, 1991: 71). In contrast, exploration alliances focus more heavily on the development of new knowledge, and thus are likely to experience greater uncertainty and variation in outcomes (Levinthal and March, 1993). Or, as March's (1991: 71) states, 'exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation.' From this dichotomy emerges a different prediction regarding the effect collaboration has on the liquidity needs of a partnering firm. In our study, we consider alliances whose express purpose is to make incremental improvements in existing technologies to be exploitation alliances. Alliances whose focus is the discovery of new products/technology are considered exploration alliances (Benner and Tushman, 2003; Rothaermel, 2001).

We expect that exploitation alliances will reduce a firm's need to hold liquid assets. First, exploitation alliances are often formed to further develop jointly held complementary resources, offering a source of incremental revenue to alliance partners (Koza and Lewin, 1998). Knowledge asymmetries are reduced as the exploitation activities focus on developing explicit information, or knowledge that has previously been codified (Rothaermel, 2001; March, 1991). By definition, exploitation activities build on existing knowledge as the firms extend their existing technology trajectory. Because of the focus on incremental innovation, alliance partners become more efficient and proficient in their creative activities (Levinthal and March, 1993), allowing the alliance partners to extend their existing capabilities and focus on specific markets or products.

Exploitation alliances are expected to experience increased efficiency, resulting in an increased level of output developed from established technologies. Moreover, the incremental changes associated with exploitation are considered 'certain, positive and close in time' (Benner and Tushman, 2002 : 682). This reduces knowledge asymmetries and uncertainty and enables exploitation alliance partners to become uniquely positioned to establish their reputations as *experts* in their fields (March, 1991). Uncertainty is further reduced as exploitation alliances are known for monitoring and measuring performance and goals are often set as measurable objective outcome controls (Koza and Lewin, 2000). Generally, the outcomes of such alliances entail the increased explicitness of knowledge rather than the uncovering of significant amounts of new knowledge. As such, knowledge asymmetries between the firm and external suppliers of capital should be reduced. Forming exploitation alliances, therefore, should reduce the R&D-intense firm's need to hold liquid assets.

Hypothesis 3: There is a negative relationship between a firm's exploitation partnering activity and its need to hold liquid assets, such that the higher the number of exploitation alliances formed in a year by the firm, the lower will be its need to hold liquid assets.

Whereas exploitation alliances typically entail clear-cut outcomes, exploration alliances are often

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formed as open-ended codevelopment projects, and entail venturing into unknown technologies, products, and markets with less objective goals and direction (Koza and Lewin, 2000). In general, exploration activities are directed toward exploring new opportunities, for the 'pursuit of new knowledge' (Levinthal and March, 1993 : 105). Exploration alliances, therefore, are associated with higher levels of risk and uncertainty (e.g., March, 1991).

Furthermore, exploration often requires some degree of novel focus as firms seek to extend the use of their technologies beyond their primary field of understanding. In order to engage in exploration, firms must, therefore, possess an adequate level of absorptive capacity to recognize and evaluate the potential of new and divergent knowledge (Cohen and Levinthal, 1990). Furthermore, to pursue unknown technologies, firms may be forced to form partnerships with those whom they have had no prior experience (Lavie and Rosenkopf, 2006). Because of the knowledge disparities between partners, more learning can take place (Gupta *et al*., 2006). Consequently, the reliance on unknown technologies and markets will create greater knowledge asymmetries between the firm and external parties. Therefore, as with any R&D-based exploration activity, we expect exploration alliances to heighten the need for firms to hold liquid assets.

Hypothesis 4: There is a positive relationship between a firm's exploration partnering activity and its need to hold liquid assets, such that the higher the number of exploration alliances formed in a year by the firm, the higher will be its need to hold liquid assets.

RESEARCH DESIGN AND METHODOLOGY

Sample selection

We conducted two sets of analyses. In our first set (liquidity analyses), we focus on how R&D investment, patenting, and exploitation and exploitation alliances affect liquid cash holdings. In our second set (R&D analyses), we examine how a firm's R&D investments are affected by its liquid asset holdings. Our sample is drawn from a population of U.S.-based biotechnology firms engaged in novel drug discovery for the years 1991–1999. Data availability constraints (i.e., access to financial and patent data) limited the sample to 180 firms. The final sample used in our liquidity analyses consisted of 1,016 firm-year observations (assembled in unbalanced panels), and 994 firm-year observations in our R&D analyses. Differences in the sample were, as described below, due to the fact that while our liquidity analyses involved regressors measured contemporaneously, our R&D analyses involved a lagged regressor. We obtained all patent information from the National Bureau of Economic Research (NBER) Patent Citations database (Hall, Jaffe, and Trajtenberg, 2001), and the United States Patent and Trademark Office's (USPTO) Cassis database. All other data were taken from Compustat datafiles, the Center for Research in Security Prices (CRSP) U.S. stock database, Windover Information Inc.'s RX Deals database, the IMS R&D Focus database, Spectrum Institutional Ownership files, and United States Securities and Exchange (SEC) proxy (DEF 14a) filings.

We first describe the variables involved in our liquidity analyses. We then describe the variables used in R&D analyses.

Liquidity analyses

Outcome variable: liquidity. Following Kim, *et al*. (1998), we measured *liquidity* as a firm's cash and equivalents (e.g., cash and marketable securities) in a specific year divided by the book value of total assets in that same year.

Predictor and control variables

R&D intensity. For each year, we calculated *R&D intensity* by dividing the firm's yearly R&D expenses by total assets in that same year. *R&D intensity* has frequently been used to gauge the fervor with which a firm pursues R&D and knowledge creation efforts (Cohen and Levinthal, 1990).

Patent value. Economically valuable knowledge accumulation should be reflected not only in the number of patents that a firm has, but also by the patents' usefulness and productivity (Trajtenberg, 1990). A firm with more knowledge capital signals to the market its superior ability in utilizing

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R&D expenditures. We calculate the value of the firm's successful patent filings, *patent value,* in the following manner:

1. We count the number of times each of a firm's patents is cited in the years following the date of patent filing.[2] Since the NBER Patent Citations database used in this study contains data through 2002, our count of 'subsequent' citations ends after 2002. Similar to academic journal articles, a patent that receives a relatively large number of citations by subsequent patents is considered to be more 'important' or 'noteworthy' than patents that receive fewer citations (Hall *et al*., 2005; Trajtenberg, 1990).
2. We then divide each patent's citation count by the mean patent citation count for all patents produced by all U.S. publicly traded biotechnology firms we identified in that patent's year of filing and technological class. More recently issued patents, due to lower exposure time, may receive fewer citations than older patents. Furthermore, the USPTO assigns each patent to one or more 'classes' in order to group patents containing 'similar subject matter' (USPTO, 2008: 5). Class categorizes patents into technological areas of invention. Certain classes of patents will demonstrate greater rates of patenting and technological advancement than others (Griliches, 1990; Trajtenberg, 1990). Standardization with class and file date issues in mind allows us to control for these issues.
3. For each year, we then add together all of the firm's standardized patent citation values. This represented the patent 'flow' created by the firm *in that single year.*
4. We then add to this yearly value the previous four years' flows to generate a 'stock' of patent value. Stocks have been used frequently in the patent-based innovation research (e.g., Henderson and Cockburn, 1994). The advantage of constructing patent value as a stock is that it provides us with a multiyear (current and past years) aggregate of patent value activity that reflects not only the signaling value of a current year's patents, but also the signaling value that remains from previous years.

[2] As is common practice in the academic literature, we assign patents to a particular year utilizing the patent application filing date rather than the later patent grant date. We use application filing date due to evidence indicating that this filing date more accurately reflects the date on which the knowledge was actually developed, and to control for the probability that much information 'leaks' upon filing and may be 'old news' by the time of granting (e.g., Griliches, 1990; Hall *et al*., 2005; Hsu and Ziedonis, 2007).

Exploitation alliances

Using Windover Information Inc.'s RX Deals database, we identified all alliances formed by firms in our sample during the sample period. For each year, we then counted all alliances formed in that year that focused on marketing, licensing, and commercialization of an existing technology to calculate our yearly *exploitation alliances* variable.

Exploration alliances

We also used Windover Information Inc.'s RX Deals database to calculate our e*xploration alliance* variable. First, we identified all alliances formed by firms in our sample during the sample period. From this pool, we retained only alliances whose primary focus was the discovery of new technology. In some cases, exploration alliance partners that discovered new technologies would subsequently engage in exploitation activities. We considered these to be exploration alliances since discovery would precede commercialization, and any commercialization was contingent on successful exploration outcomes. We counted the number of exploration alliances formed in each year for each firm in our sample.

We controlled for the size of the firm, as firm size may explain a firm's liquid asset holdings, R&D expenditures, and firm performance. For example, size may increase legitimacy and therefore access to financial capital. We use the natural log of the firm's book value of yearly total assets to measure *firm size*. We divide the book value of total debt in a single year by the book value of total invested capital in that same year to calculate *leverage*. Kim *et al*. (1998) argue that as a firm's leverage increases, the firm's cost of borrowing increases. Monitoring and ownership by institutional investors such as banks, insurance companies, and pension funds may affect the degree to which external capital providers (including these same institutions) are willing to fund the firm's operations. We calculate *institutional percentage* by computing the level of common equity held by institutions in a single year as a percentage of the firm's total outstanding common equity in

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that year. We obtained data on institutional ownership from Spectrum files. Monitoring by outsiders (i.e., non-managers/chairs) on the board of directors can affect the degree to which external capital providers are willing to fund the firm's operations. We calculate the *outside director ratio* by dividing the number of outside directors on a firm's board in a single year by the number of inside (i.e., top manager) board members in that year. We obtained data to calculate this variable from SEC Def 14a filings. *Burn rate*, or the speed with which a company uses its cash, is calculated by subtracting the previous year's cash and equivalents balance from the current year's cash and equivalents balance, and then dividing this number by the previous year's cash and equivalents balance. Burn rate is an often used to estimate the speed with which a biotechnology firm uses its cash (e.g., Jacobs, 2002).

We also included product milestones controls (e.g., Gulati and Higgins, 2003; Lerner *et al*., 2003) as these may affect liquidity held by a biotechnology firm. *Preclinical, FDA phase I, FDA phase II, FDA phase III, FDA approved*, and *marketed drugs* variables were constructed using data from the IMS R&D Focus database to capture a firm's progress from the idea stage to therapy commercialization. *Preclinical* refers to the number of significant animal and related studies in which a firm is engaged in a single year. Preclinical studies are designed to generate data used to convince the United States Food and Drug Administration (FDA) that subsequent clinical-trial testing on a drug candidate is warranted, or to defer/abandon/alter further testing. If preclinical trials demonstrate a potential for therapeutic efficacy, firms can apply to the FDA for permission to further test a drug candidate's effects on human subjects.[3] *FDA phase I* represents a count of the number of a firm's drugs that are currently in phase I FDA clinical trials in the focal year. In phase I trials, the drug candidate is administered to healthy volunteers in order to test for safety, and to provide information on dosing in later stages of testing. If a firm successfully completes phase I trials, it can seek approval to proceed to phase II trials. *FDA phase II* represents a count of the number of a firm's drug candidates in phase II clinical trials in that focal year. Phase II trials involve human subjects that are afflicted with the condition that the drug candidate is designed to treat, and provide additional safety information as well as initial efficacy information. After completion of phase II, a firm may be approved by the FDA to proceed to phase III trials. *FDA phase III* is a count of the number of drugs a firm has in phase III clinical trials in a single year. Phase III trials, conducted on afflicted volunteers, provide therapeutic efficacy information and form the basis on which new drug applications are approved by the FDA. *FDA approved* refers to the number of approved but not marketed drugs a firm has in the focal year. Finally, *marketed drugs* refers to the number of marketed drugs a firm has in a single year.

We also control for the degree to which the firm's R&D activities rely on *external finance*. To calculate this number, we divide the total annual net cash flows from external financing activities (e.g., borrowing, equity issue) as indicated in the firm's annual cash flow statement by the firm's yearly R&D expense.

We use *Tobin's q* to measure firm performance. Tobin's q is a theoretically and intuitively useful measure of performance because it compares the firm's market value to its replacement value of its assets. Thus, if q is greater than unity, the firm is perceived by the market to be performing well. Firms with greater performance may have greater reputations and thus, greater access to cash. We measure Tobin's q as the sum of the firm's market value of equity, book value of preferred stock, and book value of total debt in a single year, divided by the book value of its total assets in that same year. Following Kim *et al*. (1998), we control for the *return spread*, or the relative attractiveness of the firm's assets vis-à-vis cash. This is measured yearly in the following manner:

[(Firm earnings before depreciation, interest, and taxes—nonoperating income)/total assets] —yearly United States Treasury Bill rate.

We include a one-year *lagged (liquidity) dependent variable* to control for other omitted variables (Greene, 2000), as well as for the possibility that liquidity levels in the previous year may affect liquidity levels in the subsequent year. Since a

[3] We focus on FDA milestones (as opposed to approval by non-U.S. regulatory agencies) when constructing our regulatory variables due to the fact that the United States is the largest and most profitable market in the world for ethical pharmaceuticals (e.g., Banerjee, 2007). Therefore, FDA approval will likely provide a robust measure of therapeutic progress as firms will most likely seek regulatory approval in the United States (in addition to other markets).

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current year's liquidity levels may reflect activities or strategic decisions in a previous year (e.g., royalty payments from a licensor, strategic decisions made by managers to maintain liquidity at levels expected by investors, etc.), a lagged liquidity variable's inclusion in our model is a necessary control. This assumption is consistent with results found by Opler *et al*. (1999: 19) who find that 'cash balances are mean reverting [and that firms tend] to not let cash balances rise too high or fall too low.' In short, a lagged dependent variable allows us to model persistence or partial adjustment of the liquidity dynamics over time (Wawro, 2002).

R&D analyses

We use *R&D intensity* as our outcome measure of R&D investments (Scellato, 2007). For our predictor variable, we use the *one-year lagged value of liquidity*, reflecting the belief that cash reserves precede investment and enable R&D expenditures in the subsequent period (see also Hao and Jaffe, 1993; Scellato, 2007). *Tobin's q* is inserted in our model since investors' perceptions of firm performance may affect that firm's access to cash and thus its ability to fund R&D. *Exploitation alliances* and *exploration alliances* may reflect a firm's research efforts as well as its commercialization attempts. We control for l*everage* since firms may have differential access to debt or equity, which in turn may affect the firm's ability to fund R&D (Scellato, 2007). *Size* may reflect a firm's legitimacy and, thus, its ability to procure resources of various types. *Burn rate* and e*xternal finance* are included in this regression to further reflect financial constraints on a firm's ability to invest in R&D. Finally, we include a *one-year lagged (R&D intensity) dependent variable* because empirical research indicates a tendency for firms to attempt to equally distribute R&D expenses over time in order to avoid hiring knowledge workers and then face resource scarcity necessitating their subsequent firing (Hall, 2005).

Model and estimation

As our data have both cross-sectional and time series (from the years 1991 to 1999) elements, we estimated the models using regression techniques for panel data (e.g., Greene, 2000). Furthermore, since our panel data models include a lagged dependent variable, a potential inconsistency in our estimation arises due to the probability that the lagged dependent variable is correlated with the error term (Greene, 2000). Arellano and Bond (1991) developed a generalized method of moments (GMM) estimator using the approach of instrumental variables to address this problem, and Blundell and Bond (1998) further refined the GMM estimator to increase efficiency. Briefly, the Blundell and Bond (1998) estimator, which we employ in our regression analyses, uses lags of the predictor variables in the regression model as well as these variables' first differences (i.e., the result from subtracting the current year's level of a variable from the previous year's level) as instruments for the predictor variables. A valid instrument, by definition, is uncorrelated with the estimation's error term, but is highly correlated with the variable to be instrumented. These demands, in turn, establish a set of requirements or 'moment conditions' that form the basis of the GMM estimation used. GMM estimates values for the model parameters in a manner that satisfies these moment conditions as closely as possible. For example, regression coefficients in our models are estimated in a manner that, among other things, makes the correlation between a first differenced lagged dependent variable (used as an instrument) and an error term as close to zero as possible.[4] Furthermore, the Arellano-Bover method incorporates a panel-specific (i.e., firm) fixed effect. Moment conditions are met only if the zero correlation between the instrumenting variables and these fixed-effects conditions are met.

As we discuss below, we provide tests of the effectiveness of our instruments and, consequently, the GMM technique we use. Furthermore, through this procedure, we can mitigate the effects of any simultaneity bias that might arise in our liquidity analyses from the idea that R&D intensity is also determined by our liquidity outcome variable, and in our R&D analyses from the idea that liquidity is also determined by our R&D outcome variable.[5]

[4] For a more detailed mathematical derivation of this result, see Arellano and Bover (1995) and Blundell and Bond (1998).

[5] Simultaneity bias can arise when an explanatory variable is simultaneously determined with an outcome variable. In such cases, bias and inconsistency are introduced in coefficient estimation. For example, we can write a simple regression model for a population relating R&D to liquidity as $liq = \beta_0 + \beta_1 R\&D_1 + \mu$. Three key conditions that must be met to consistently estimate β_1 are (i) the selection of a random sample from the population,

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ANALYSES AND RESULTS

Tables 1a and 1b provide the means, standard deviations, and correlations of the variables used in our empirical models. Tables 2 (R&D analyses) and 3 (liquidity analyses) present the results of our empirical estimations. The chi-square statistics for all models are significant at the $p < 0.001$ levels. Tables 2 and 3 also report the results of Sargan tests and *C* tests. The Sargan statistic provides a test statistic in the context of GMM that no correlation between the instruments and the error term exist. Since valid instruments must be uncorrelated with the error, a rejection of the null hypothesis of no correlation (i.e., statistical significance of the Sargan statistic) indicates poor suitability of the model (Hansen, 1992). None of these tests are significant, indicating the orthogonality of our instruments to the error term, and the suitability of our models. The *C* statistic in the GMM context provides a result of the test of the null hypothesis that a subset of the instruments is orthogonal to the error term and is a significant contributor to the explanation of the endogenous variables (Hayashi, 2000). In short, the *C* test compares full and restricted models to assess the orthogonality of instruments included in the full model but excluded in the restricted model. Like a partial F-test in ordinary least squares, the *C* statistic provides a test of whether addition of new predictor variables significantly improves the explanatory power of the model.

Regarding our liquidity analyses, the *C* statistic is not significant in Models 2–4 of Table 3, suggesting that the addition of R&D intensity in Model 2, patent value, exploration alliances, and exploration alliances in Model 3, and the R&D intensity × patent value interaction in Model 4 significantly enhances the models' explanatory powers. We should note that, as in the cases of Models 2 and 4, the *C* statistic can assume negative values. Since the *C* test is calculated by subtracting the Sargan statistic of the restricted model from that of the unrestricted model, a negative *C* test can result because the restricted and unrestricted models do not use the same covariance matrix of orthogonality conditions. Negative test statistics still lead to a failure to reject the null hypothesis and thus support inclusion of our main effects and interaction variables added in Models 2–4 (see Hayashi, 2000: 220).

Regarding control variables in our liquidity analyses, burn rate is a significant predictor of liquidity in all models. One might expect that the more rapidly a firm consumes cash, the lower its cash reserves (i.e., liquidity) would be. However, an increasing dependence on cash may make cash shortfalls especially detrimental to vitality, prompting the highly cash-dependent firm to do everything in its power to preserve a margin of safety via higher cash reserves. We also found external finance to be a positive and significant predictor of liquidity. This might be due to the 'lumpiness' of the cash procurement process in our sample. An examination of the Windover Information Inc.'s RX Deals database (from which, as noted, we also obtained alliance data) as well as other data sources gives some indication of the infrequency with which external cash is raised by our sample. Successful cash management requires the storing of cash to invest when cash procurement becomes more difficult, as opposed to the rapid spending when easily procured (Baumol, 1952).

Institutional percentage is a negative and significant predictor of liquidity in our models. This is not surprising since research demonstrates the monitoring properties of institutional investors in the R&D context (e.g., Hansen and Hill, 1991). In the setting we examine, it appears that institutional monitoring provides legitimacy to the firm's operations, thereby allowing the firm to lower its cash reserves. We found firm size to be a positive and significant predictor of liquidity. Although Kim *et al.* (1998) found size to have an insignificant effect on liquidity, Opler *et al.* (1999) found size to be a negative and significant predictor of liquidity. However, whereas Opler *et al.*'s (1999) sample consists of firms across multiple industries, our sample consists of a single, R&D-intensive industry. We surmise that in an industry where product development is highly uncertain, larger firms may use their more significant resources to store

(ii) a conditional mean for the error, μ, of zero (i.e., $E(\mu) = 0$), and (iii) a lack of correlation between the error in the population and the regressor, $R\&D_1$ (i.e., $\mathrm{Cov}(R\&D_1, u) = 0$). The conditions suggest that unobserved factors involved in the regression are not systematically related to the observed factors. Otherwise, $E(\mu) \neq 0$ (and, by implication $\mathrm{Cov}(R\&D, u) \neq 0$), and the estimated regression coefficient, β_1, will likely be biased and inconsistent. Because we expect R&D to be determined by liquidity as well as liquidity to be determined by R&D, we will likely violate these conditions since $\mathrm{Cov}(R\&D, u) \neq 0$. Effective use of the Blundell and Bond (1998) estimator should curtail this problem since it is predicated on, among other things, minimizing $\mathrm{Cov}(R\&D, u)$.

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Table 1a. Simple statistics and correlations[a]

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	**Liquidity**	0.63	0.27													
2	**R&D intensity**	0.35	4.38	0.04												
3	**Patent value**	20.28	66.25	−0.18***	−0.02											
4	**Explor. alliances**	0.92	1.46	0.02	−0.03	0.19***										
5	**Exploit. alliances**	0.30	0.69	−0.12***	−0.02	0.18***	0.16***									
6	**R&D int. × pat. val**	2.17	4.58	0.01	−0.02	0.57***	0.27***	0.10***								
7	**Burn rate**	2.29	36.44	0.05	−0.001	−0.02	−0.03	−0.03	−0.03							
8	**External finance**	1.93	4.65	0.06+	−0.02	−0.07*	−0.04	0.02	−0.10***	0.21***						
9	**Tobin's q**	5.26	6.35	−0.09*	−0.03	−0.07*	0.00	0.01	−0.06+	−0.00	0.03					
10	**Instit. pct.**	17.63	21.21	−0.09*	0.00	0.36***	0.09*	0.17***	0.28***	−0.05	−0.09***	−0.09***				
11	**Outside dir. ratio**	1.58	2.25	0.05	0.01	0.09*	0.05	−0.03	0.13***	0.03	−0.04	−0.10***	0.11***			
12	**Leverage**	0.08	1.22	−0.01	−0.00	0.04	0.03	−0.09***	0.05+	−0.00	0.01	−0.03	0.05	0.01		
13	**Return spread**	−4.75	2.26	0.04	0.02	0.03	0.08*	0.07*	0.04	−0.01	−0.02	−0.15***	0.13***	−0.20***	0.03	
14	**Firm size**	11.30	1.27	−0.30***	−0.17***	0.49***	0.33***	0.24***	0.38***	−0.09***	−0.14***	−0.20***	0.45***	0.11***	0.09***	0.20***
15	**Preclinical**	2.91	4.58	0.02	−0.03	0.23***	0.37***	0.14***	0.40***	−0.00	−0.07*	−0.04	0.25***	0.06+	0.06+	0.07+
16	**FDA phase I**	0.42	0.77	0.11***	−0.02	0.05+	0.26***	0.07*	0.23***	−0.03	−0.09*	0.03	0.08*	0.05	0.03	0.06+
17	**FDA phase II**	0.39	0.89	−0.10***	−0.02	0.37***	0.31***	0.11***	0.42***	−0.03	−0.09***	0.01	0.22***	0.05+	0.04	0.09*
18	**FDA phase III**	0.23	0.66	−0.12***	0.05	0.29***	0.21***	0.16***	0.33***	−0.02	−0.07*	−0.02	0.14***	0.07*	0.04	0.05
19	**FDA approved**	0.00	0.05	0.04	−0.00	−0.01	0.00	0.00	−0.02	−0.00	−0.00	−0.02	−0.01	−0.02	0.00	−0.00
20	**Mrkt. drugs**	0.19	0.89	−0.20***	−0.01	0.35***	0.23***	0.36***	0.23***	−0.01	−0.01	−0.02	0.26***	0.04	0.05	0.05
21	**Lagged liquidity**	0.63	0.27	0.70***	0.03	−0.17***	0.04	−0.07*	0.03	−0.12***	−0.16***	−0.01	−0.02	0.04	−0.04	−0.05+

Table 1b. Simple statistics and correlations continued[b]

		14	15	16	17	18	19	20
15	**Preclinical**	0.40***						
16	**FDA phase I**	0.18***	0.45***					
17	**FDA phase II**	0.40***	0.50***	0.32***				
18	**FDA phase III**	0.35***	0.32***	0.20***	0.46***			
19	**FDA approved**	0.001	0.01	0.07*	−0.02	−0.02		
20	**Mrkt. drugs**	0.38***	0.32***	0.09***	0.30***	0.42***	−0.01	
21	**Lagged liquidity**	−0.22***	0.07*	0.12***	−0.07*	−0.09*	0.03	−0.16***

[a] $n = 1016$
[b] Burn rate was rescaled as burn rate/100. R&D intensity was rescaled as R&D intensity/ 1000.
* $P < 0.050$
** $P < 0.010$
*** $P < 0.001$

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Table 2. Dynamic panel data estimation of the effects on R&D intensity of liquidity$_{t-1}$[a,b]

Variables	Model 1
Lagged liquidity	83.277*
	(39.349)
Patent value	−0.087
	(0.114)
Tobin's q	−0.616
	(1.399)
Exploration alliances	−2.061
	(4.583)
Exploitation alliances	9.399
	(8.997)
Leverage	3.075
	(1.631)
Firm size	−8.488
	(5.056)
Burn rate	−0.422
	(0.315)
External finance	−1.725
	(1.443)
Lagged R&D intensity	0.925***
	(0.035)
Chi-square	2890.134***
Sargan statistic	33.759

[a] $n = 994$
[b] Standard errors in parentheses; coefficients of year and firm fixed effects omitted from table. Burn rate was rescaled as burn rate/100. R&D intensity was rescaled as R&D intensity/1000.
* $P < 0.050$
** $P < 0.010$
*** $P < 0.001$

cash to use when the costs of external cash procurement are especially high. Smaller firms may not be able to avail themselves of such advantages.

We find the number of preclinical studies in Models 2–4 to positively affect liquidity held by the firm. This may arise from the fact that preclinical testing in animal models is a form of exploration, and therefore increases information asymmetries between the firm and shareholders. The number of a firm's drug candidates in FDA phase I trials also positively and significantly affects liquidity levels. This may reflect the receipt of milestone payments awarded to the firm upon successful commencement of FDA clinical trials and the resulting enhanced cash position. This may also stem from the fact that although reaching phase I trials is a positive accomplishment, ultimate success is highly risky and costly. Indeed, only about 20 percent of all drug candidates that enter phase I will gain marketing approval from the FDA, but a firm can expect to spend about $400 to $800 million from preclinical stages through approval (DiMasi, Hansen, and Grabowski, 2003). Entering phase I, therefore, indicates the beginning of a potentially long, costly, and highly uncertain process that necessitates the building of cash reserves. The FDA phase II trials coefficient is significant in Model 1 but becomes insignificant when controlling for R&D intensity. The number of candidates in FDA phase III trials is significant and negative in three of our models (Models 2–4, Table 2). Since approximately 68.5 percent of therapies in phase III proceed to the market approval stage, a reduction in held cash at this point may stem from the therapy's proximity to approval. Surprisingly, we find the number of FDA-approved drugs to be an insignificant predictor of liquidity. However, one might argue that FDA phase III already contains information regarding approval, and that investors look to subsequent marketing in the form of marketed drugs (also a significant and positive determinant of liquidity) to adjust their willingness to finance R&D efforts.

Finally, we found the lagged liquidity variable to be a positive and significant predictor of liquidity. This is consistent with the notion that current liquidity levels are a function of past levels (see Opler *et al*., 1999: 19)

We based our study on previous research that finds that measures of liquidity predict R&D investment (Hao and Jaffe, 1993; Himmelberg and Petersen, 1994; Scellato, 2007), and studies indicating that R&D investment determines liquid cash holdings (Kim *et al*., 1998; Opler *et al*., 1999; Papaioannou *et al*., 1992). As indicated in Table 2, we find lagged liquidity (83.277, $p < 0.05$) to be a positive and significant predictor of R&D intensity.

In addition, results presented in Table 2 indicate that R&D intensity positively and significantly predicts liquidity. Support for this latter relationship is found in Models 2 (other main effects excluded) and 3 (all main effects included), as the coefficient of the R&D intensity variable is positive and significant (Model 2, 0.081, $p < 0.001$; Model 3, 0.085, $p < 0.001$). In short, our results indicate that R&D intensity positively predicts liquidity, and liquidity lagged one year positively predicts R&D intensity.

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Table 3. Dynamic panel data estimation of the effects on liquidity of R&D intensity, patent value, exploration alliances, and exploitation alliances [a,b]

	Model 1	Model 2	Model 3	Model 4
R&D intensity		0.081***	0.085***	0.090***
		(0.024)	(0.022)	(0.022)
Patent value			−0.001***	−0.001
			(0.000)	(0.000)
Exploration alliances			0.007*	0.008**
			(0.003)	(0.003)
Exploitation alliances			−0.015**	−0.016**
			(0.006)	(0.006)
R&D int. × patent value				−0.008*
				(0.004)
Burn rate	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
External finance	0.009***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Tobin's q	−0.002**	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Institutional percentage	−0.001***	−0.002***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Outside director ratio	0.002	0.001	0.000	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
Leverage	0.008	0.006	0.005	0.006
	(0.005)	(0.005)	(0.004)	(0.004)
Return spread	−0.000	0.011	0.012	0.012
	(0.006)	(0.007)	(0.007)	(0.007)
Firm size	0.026***	0.042***	0.044***	0.045***
	(0.004)	(0.006)	(0.006)	(0.006)
Preclinical	0.001	0.003*	0.003*	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
FDA phase I	0.027**	0.040***	0.038***	0.042***
	(0.009)	(0.009)	(0.008)	(0.008)
FDA phase II	−0.019*	−0.013	−0.009	−0.005
	(0.008)	(0.008)	(0.007)	(0.008)
FDA phase III	−0.012	−0.069***	−0.069***	−0.068***
	(0.010)	(0.019)	(0.018)	(0.017)
FDA approved	0.103	0.108	0.113	0.107
	(0.092)	(0.084)	(0.082)	(0.082)
Marketed drugs	−0.035***	−0.034***	−0.028***	−0.032***
	(0.009)	(0.008)	(0.008)	(0.008)
Lagged liquidity	0.527***	0.352**	0.317**	0.307**
	(0.115)	(0.116)	(0.112)	(0.112)
Chi-square	16403.703***	19690.138***	20587.821***	20866.409***
Sargan statistic	39.947	36.126	37.022	35.212
C-statistic		−3.821	0.896	−1.802

[a] $n = 1016$
[b] Standard errors in parentheses; coefficients of year fixed effects omitted from table. Burn rate was rescaled as burn rate/100. R&D intensity was rescaled as R&D intensity/ 1000.
* $P < 0.050$
** $P < 0.010$
*** $P < 0.001$

Per Hypothesis 1, we predicted that patent value would negatively predict liquidity. Support for this hypothesis is found in Model 3, as the coefficient of the patent value variable is negative and significant (−0.001; $p < 0.001$). Per Hypothesis 2, we also expected patent value to negatively moderate the liquidity-R&D intensity relationship. Support is found in Model 4 where the coefficient

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of the R&D intensity × patent value interaction is negative and statistically significant (−0.008; $p < 0.05$).[6]

Figure 1 graphically confirms this relationship. On this graph, the low patent value line corresponds to patent value at the 25th percentile value, the median patent value line corresponds to patent value at the median value of patents, and the high patent value line corresponds to the 75th percentile value. R&D intensity is plotted on the x-axis and liquidity is plotted on the y-axis. The line representing the R&D intensity × liquidity relationship under low levels of patent value is positively sloped. As R&D intensity increases at low patent value, liquidity demands increase. These liquidity demands are less severe at the median level of patent value, indicating that median patent value decreases liquidity demands in the presence of R&D. Note, however, that the line depicting median patent value still appears to be positively sloped, suggesting that liquidity demands at this level still increase as R&D intensity levels increase. Finally, in the high patent value context, as R&D increases, liquidity demands decrease. The signaling of valuable technologies (via patent value) mitigates (and appears to even reduce) the need to hold liquid assets as R&D intensity levels increase. This latter condition may result from the possibility that very high levels of patent value provide a strong enough signal that the firm can (relatively) easily procure external funds, and therefore does not need to hold cash in reserve to finance R&D.

Hypothesis 3 predicts that exploitation alliances will negatively predict liquidity. Support for this hypothesis is found in Models 3 and 4, as the coefficients of the exploitation alliances variable is negative and significant (Model 3: −0.015; $p < 0.01$; Model 4: −0.016; $p < 0.01$). Finally, Hypothesis 4 predicts that exploration alliances will positively predict liquidity. Support for this hypothesis is also found in Models 3 and 4, as the coefficients of the exploration alliances variable are positive and significant (Model 3: 0.007; $p < 0.05$; Model 4: 0.008; $p < 0.05$).

To assess robustness of our models, we substituted our patent value measure based on subsequent citation data with measures of patent value

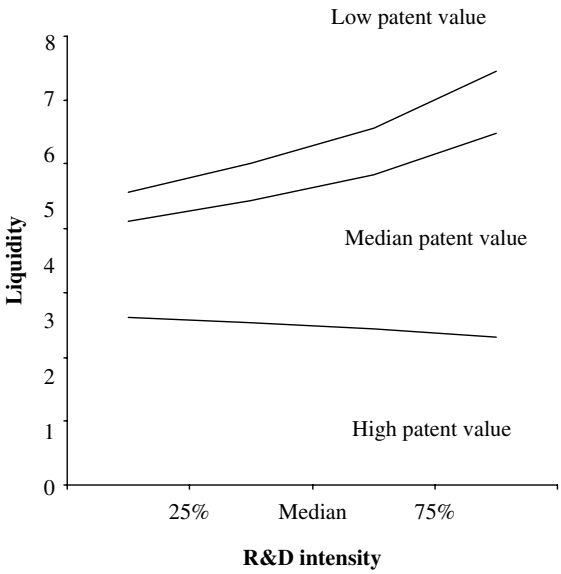

Figure 1. Effect of R&D intensity × patent value interaction on liquidity

based on patent subclass and claims information.[7] As noted, the USPTO assigns each patent to one or more 'classes' in order to group patents containing 'similar subject matter.' The USPTO further subdivides these approximately 400 class categorizes into approximately 100,000 subclasses. Following McGrath and Nerkar (2004), we used patent subclass data to measure patent scope, or the overall breadth of protection provided by a patent. Lerner (1994a) demonstrates that patent scope (operationalized in his study as the number of different International Patent Classification [IPC] classes to which a single patent is assigned) positively and significantly affects patent value. Lerner argues that the number of different technology classes assigned to a patent proxies for the number of different technologies that are 'protected' by that patent, and thus is an indicator of ultimate value. Similar to the citation-based patent-value operationalization used in our core models, we weighted each patent assigned to our sample firms between 1986 and 1999 (the years from which we construct our patent-based variables) by the number of unique subclasses that patent obtained, and created five-year stock measures of patent value as indicated by subclass diversity. Test of our hypotheses

[6] Repeating this estimation with centered main effects involved in the interaction (Aiken and West, 1991) provides the same support for our hypothesis test.

[7] We thank two anonymous reviewers for suggesting these types of robustness checks.

utilizing these subclass-based measures of patent value demonstrate support for our hypotheses.

Using patent claims data, we further assess robustness of our patent value variable as well as the ability for investors to gauge the ultimate merit of patenting activity. According to Tong and Frame, (1994: 134), a patent's 'claims' delineate the novel features protected in a patent. For example, a patent on an arthritis drug might contain one claim for the specific therapeutic compound as well as one claim for the mechanism by which the drug is delivered within the human body (McGrath and Nerkar, 2004: 9). The number of claims (and thus inventions) contained within a patent therefore should be a proxy for overall value, and empirical evidence provides support for this assertion. Nerkar and Paruchuri, (2005) find that the likelihood of a patent being cited by a subsequent patent (and thus indicating its worth) is positively and significantly influenced by the number of claims it possesses. Lanjouw and Schankerman (2001) find that the number of claims contained in a patent as well as the number of citations that patent receives by subsequent patents, positively affect the probability of that patent being litigated. Since previous research suggests that probability of litigation increases as the 'size of the stakes' or value of the invention increases (Lanjouw and Schankerman, 2001: 132), these results support the idea that claims counts are a robust indicator of patent value. Similar to our subclass variable, we created a patent value measure based on claims data. Empirical analyses utilizing this variable also provide support for our hypotheses.

Lerner *et al*. (2003) demonstrate that the distribution of contractual rights among alliance partners varies depending on how receptive capital markets are to equity financing. In short, alliance partners may substitute for public financing when public financing is available only at excessive costs. To assess the impact of equity markets' willingness to fund a biotechnology firm, we substitute our year controls with a *Lerner Index* (Lerner, 1994b; see also Gulati and Higgins, 2003). Following Lerner (1994b) we construct an equal dollar index of 13 biotechnology stocks (rebalanced annually) to gauge willingness. Our hypotheses are also supported when we include this index in our models. However, the Sargan statistic associated with these models is positive, indicating a poor fit of the models.

DISCUSSION AND IMPLICATIONS

We set out to examine factors that impact the management of liquid assets, specifically by demonstrating how the signaling and cash flow properties of patents and alliance forms affect a firm's need to hold cash. Effective management of liquid assets (e.g., cash and equivalents) is critical to success in research-intensive industries and requires a balancing of demands by both the firm's competitive environment and governance costs associated with this environment. The results reported herein support this assertion. We find that, consistent with prior research (Kim *et al*., 1998; Opler *et al*., 1999; Papaioannou *et al*., 1992), the level of a firm's R&D intensity is positively related to the level of liquid assets held internally by the firm. We interpret this to mean that research-intensive firms, due to invention-induced knowledge asymmetries, face considerable costs when attempting to obtain capital from external capital markets. Holding relatively high levels of liquid assets allows research-intensive firms to lessen these costs by reducing dependence on external capital markets for cash.

However, we found that signaling and cash flow properties of a firm's patenting activity may also reduce costs of capital procurement. We believe that patents accomplish this by providing the potential for near term cash flows, and by indicating to external capital providers the firm's ability to create new and potentially valuable knowledge. It is worth noting that holding liquid assets appears to be impacted by the value of previous patenting activity. For example, based on our empirical results, lower valued patents may actually require holding higher levels of liquid assets as patents with no value may send negative signals to external constituents. Conversely, plotting of our R&D intensity $\times$ patent value interaction seems to indicate that higher valued patents send out signals of the firm's inventive prowess, reducing knowledge asymmetries, perhaps by reducing financial capital procurement costs. Importantly, we believe that as external capital providers' faith in the abilities of the firm and their understanding of the firm's research activities grow due to explicit signals conveyed by valued patents, the costs these providers charge for capital decreases. As such, high valued patenting stock is negatively related to liquidity, and negatively moderates the relationship between R&D intensity and liquidity.

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We also examined the impact of alliance activity on the level of liquid assets as firms are increasingly relying on alliance partners to create new inventions. We examined both exploitation and exploration alliances and how the two may differ in the amount of knowledge asymmetries they create. As predicted, exploitation alliances, those alliances whose primary purpose is to further existing technology, reduce the level of cash balances the firm needs to set aside for future projects. Exploitation alliances rely on existing knowledge, thus knowledge asymmetries appear to be less of a problem and less risk is associated with the inventive activity. Conversely, exploration alliances focus on discovering new knowledge and technologies. As such, exploration alliances should increase knowledge asymmetries and impose more risk. To reduce the costs associated with raising external funds, we interpret our results to indicate that higher levels of liquid assets must be held.

Limitations and future directions

We attempted to elucidate the signaling effects of patenting and alliance activity on liquidity management. Specifically we argued that valuable patenting activity can reduce information asymmetries as well as raise the prospect of future cash flows. An issue that arises with this interpretation, however, is the difficulty in disentangling the signaling effects of patenting from the real cash flows derived from exploiting those patents. For example, one can imagine a scenario where possession of important patents provided a firm with continual cash inflows (e.g., from licensing agreements), but did not reduce information asymmetries between a firm and outside investors. Or, the same firm may choose to hold lower cash reserves in expectation of these future monetary infusions. In such instances, one might empirically observe our anticipated effects of patent ownership on liquidity levels for reasons other than the reduction of firm-investor asymmetries.[8] We believe our empirical design reasonably controls for these contingencies, but we cannot rule out confounding these effects with our hypothesized effects. Utilizing Tobin's q in our estimations effectively controls for the effects of future growth, but does so only in cases where information regarding growth is available to external investors. In some cases, private information may not diffuse to investors until some time has elapsed. To some extent, the use of relatively long panels in our empirical estimation should reduce the likelihood of such information impactedness since information should ultimately circulate to investors because of managements' desire to generate notoriety for the firms, or because of the difficulty in maintaining the secrecy of such deals (e.g., Bhattacharya and Ritter, 1983; Okuno-Fujiwara, Postlewaite, and Suzumura, 1990). Nonetheless, (expectations of) cash inflows occurring at the end of our time frame may not have had a chance to diffuse to investors, and therefore will not be imputed in our results.

One may also question the rationale of limiting cash reserves based on expectations of cash flows since even the most promising of biotech alliances have high probabilities of failure and may provide limited cash milestones (e.g., Laroia and Krishnan, 2005). Therefore, limiting cash reserves in the expectations of future cash flows may still place the firm in considerable jeopardy. Nonetheless, some firms (and their partners) may prefer to withhold such information for fear of provoking competitive entry into a given area of research. Our study, consequently, is limited in that we cannot empirically examine the effects of such desires to withhold information on liquidity. A fruitful area for future research is to examine how countervailing forces affect a firm's desire to emit signals in financially constraining circumstances.

While our study contributes to our understanding of how exploitation and exploration alliances differ in reducing the need to hold liquid assets, future research is needed to examine how the two types of alliances impact the need to hold liquid assets in various levels of financial uncertainty. Our study examined firms in a single industry. While the focus on the biotechnology industry enabled us to focus on inventive activity as a predictor of liquidity, it may limit the generalizability of our findings across multiple industries. We used patents to proxy signaling of potential innovative success and chose the biopharmaceutical industry as this industry has a high propensity to patent new innovations, and patent statistics are noteworthy measures of innovative success in this industry. However, signaling of inventive success can extend beyond patents in many industries and may be

[8] We thank an anonymous reviewer for pointing out these difficulties.

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manifest in, for example, product attributes or education achievements of managers (see for example, Backes-Gellner and Werner, 2004; Robertson, Eliashberg, and Rymon, 1995). Examining tangible outcomes of the inventive process other than patents seems necessary to extend our results to different venues.

Furthermore, research indicates the need to focus on a single industry when utilizing patent data due to the varied level of property right protection afforded by patents across industries as well as due to the concern that types of inventions patented may also diverge when including multiple industries in such studies (Basberg, 1987; Mansfield, 1986). For example, pharmaceutical patents in many instances cover technologies that closely resemble ultimate products (i.e., chemical structures that have some therapeutic benefit). In other industries (e.g., automobiles), patents comprise technologies that do not as closely resemble final products, but rather components or subassemblies of those products (e.g., automobile transmissions, engines). It is therefore imperative to attempt to replicate the findings of this study across other industries in which final products are protected in a more 'compartmentalized' fashion. As such, our conclusions would be strengthened by replication using samples from other research-intensive industries. Also, the identification of critical contingencies in other types of contracting environments (i.e., industries) could lead to a more generalizable theory of the determinants of liquidity.

The results presented herein provide further insight into the complexity of invention. Success in the inventive process, wherein new ideas are uncovered from previously obscured domains, is not easily achieved (e.g., Freeman, 1982; Schmookler, 1966). In addition to the difficulties imposed by regulatory requirements, the fickleness and unpredictability of consumer tastes, and the transforming of obscure ideas into economically valuable ones, research-active firms can face especially difficult costs of financing invention. Indeed, a worthwhile endeavor for future research would be to examine inventive activities that were *never* pursued due to the lack of available financial capital. Firms seem to have a portfolio of potentially worthwhile projects (e.g., Spilker, 1994); thus, it would be useful to examine the characteristics of opportunities that do not get funded, and consequently are not attempted. This would certainly provide valuable information to managers of research-intensive firms.

CONCLUSIONS

We believe this research makes several contributions to the strategy literature. First, it contributes to our understanding of the additional costs associated with holding liquid assets due to knowledge asymmetries associated with R&D. Increased knowledge asymmetries may force the firm to decide between funding or maintaining current projects, or stockpiling cash for future projects. We believe our study provides support for the idea that firms mitigate the costs associated with raising cash through external capital markets by reducing knowledge asymmetries through high valued patenting activity. In addition, our study contributes to the alliance literature. We believe that exploration alliances, due to their increased knowledge asymmetries, heighten the need to hold liquid assets, and therefore are likely to increase the overall costs of R&D, at least in the near term. On the other hand, we find that exploitation alliances do not increase the need to augment holdings of liquid assets.

Finally, our study has managerial implications. Managers must be aware of the less obvious costs associated with R&D. Managing knowledge asymmetries with important stakeholders may reduce some R&D costs and risks as well as free up needed cash for other promising R&D ventures. Due to the increasing level of inventive activity needed to compete in today's ever-changing technological environment, those firms that are best able to manage knowledge asymmetries may indeed be better positioned to obtain a competitive advantage.

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REFERENCES

Aiken LS, West SG. 1991. *Multiple Regression: Testing and Interpreting Interactions.* Sage: Thousand Oaks, CA.

Ahuja G. 2000. Collaboration networks, structural holes, and innovation: a longitudinal study. *Administrative Science Quarterly* **46**: 425–455.

Akerlof GA. 1970. The market for 'lemons': quality uncertainty and the market mechanism. *Quarterly Journal of Economics* **84**: 488–500.

Anton JJ, Yao DA. 2004. Little patents and big secrets: managing intellectual property. *RAND Journal of Economics* **35**(1): 1–22.

Arellano M, Bond S. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economics and Statistics* **58**: 277–297.

Arellano M, Bover O. 1995. Another look at the instrumental variable of error component models. *Journal of Econometrics* **68**: 29–51.

Arrow KJ. 1962. Economic welfare and the location of resources for invention. In *The Rate and Direction of Inventive Activity*, Universities National Bureau Committee of Economic Research (ed). Princeton University Press: Princeton, NJ; 609–626.

Backes-Gellner U, Werner A. 2004. Entrepreneurial signaling via education: success factor for innovative start-ups. *Small Business Economics* **29**: 173–190.

Banerjee PK. 2007. Becoming an American company: a holistic approach to decision making. *Nature Biotechnology* **25**(3): 277–280.

Barrett M. 1996. *Intellectual Property*. Emanuel Law Outlines: Larchmont, NY.

Basberg BL. 1987. Patents and the measurement of technological change: a survey of the literature. *Research Policy* **16**: 131–141.

Baumol WJ. 1952. The transaction demand for cash: an inventory-theoretic approach. *Quarterly Journal of Economics* **66**(4): 545–556.

Benner MJ, Tushman ML. 2002. Process management and technological innovation: a longitudinal study of the photography and paint industries. *Administrative Science Quarterly* **47**: 676–706.

Benner MJ, Tushman ML. 2003. Exploitation, exploration, and process management: the productivity dilemma revisited. *Academy of Management Review* **28**: 238–256.

Bhattacharya S, Ritter JR. 1983. Innovation and communication: signaling with partial disclosure. *Review of Economic Studies* **50**: 331–346.

Blundell R, Bond S. 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* **87**(1): 115–143.

Chi T, Levitas EF. 2007. An examination of options embedded in a firm's patents: value of dispersion in citations. In *Advances in Strategic Management Series (Vol.24)*, Reuer J, Tong TW (eds). Emerald Group Publishing: Bingley, UK; 405–427.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1): 128–152.

Cyert RM, March JG. 1963. *A Behavioral Theory of the Firm*. Prentice-Hall: Englewood Cliffs, NJ.

DeCarolis DM, Deeds DL. 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.

DiMasi JA, Hansen RW, Grabowski HG. 2003. The price of innovation: new estimates of drug development costs. *Journal of Health Economics* **22**: 151–185.

Dyer JH, Hatch NW. 2006. Relation-specific capabilities and barriers to knowledge transfers: creating advantage through network relationships. *Strategic Management Journal* **27**(8): 701–719.

Freeman C. 1982. *The Economics of Industrial Innovation*. MIT Press: Cambridge, MA.

Greene WH. 2000. *Econometric Analysis* (4th edn). Prentice-Hall: Upper Saddle River, NJ.

Griliches Z. 1990. Patent statistics as economic indicators: a survey. *Journal of Economic Literature* **28**: 1661–1707.

Gulati R, Higgins MC. 2003. Which ties matter when? The contingent effects of interorganizational partnerships on IPO success. *Strategic Management Journal* **24**(2): 127–144.

Gupta AK, Smith KG, Shalley CE. 2006. The interplay between exploration and exploitation. *Academy of Management Journal* **49**(4): 693–706.

Hall BH. 2000. Innovation and market value. In *Productivity, Innovation and Economic Performance*, Barrell R, Mason G, O' Mahony M (eds). Cambridge University Press: New York; 177–198.

Hall BH. 2005. The financing of innovation. Available online at http://www.infra.kth.se/cesis/cesis/education/master/courses/1n1705/C_Hall.pdf.

Hall BH, Jaffe AB, Trajtenberg M. 2001. The NBER patent citations data file: lessons, insights and methodological tools. NBER Working paper 8498. National Bureau of Economic Research: Cambridge, MA.

Hall BH, Jaffe AB, Trajtenberg M. 2005. Market value and patent citations. *RAND Journal of Economics* **36**: 16–38.

Hansen BE. 1992. Consistent covariance matrix estimation for dependent heterogeneous processes. *Econometrica* **60**(4): 967–972.

Hansen GS, Hill CWL. 1991. Are institutional investors myopic? A time series study of four technology-driven industries. *Strategic Management Journal* **12**(1): 1–16.

Hao KY, Jaffe AB. 1993. Effect of liquidity on firms' R&D spending. *Economics of Innovation and New Technology* **2**: 275–282.

Hayashi F. 2000. *Econometrics*. Princeton University Press: Princeton, NJ.

Heeley MB, Matusik SF, Jain N. 2007. Innovation, appropriability, and the underpricing of initial public offerings. *Academy of Management Journal* **50**(1): 209–225.

Helfat CE. 1994. Evolutionary trajectories in petroleum firm R&D. *Management Science* **40**(12): 1720–1747.

DOI: 10.1002/smj

Henderson R, Cockburn I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal*, Winter Special Issue **15**: 63–84.

Himmelberg CP, Petersen BC. 1994. R&D and internal finance: a panel study of small firms in high-tech industries. *Review of Economics and Statistics* **76**: 38–51.

Hsu DH, Ziedonis RH. 2007. Patents as quality signals for entrepreneurial ventures. Paper presented at the DRUID Summer Conference, Copenhagen, CBS, Denmark. Available at: http://www2.druid.dk/conferences/viewpaper.php?id=1717&cf=9.

Jacobs T. 2002. Biotech follows dot.com boom and bust. *Nature Biotechnology* **20**(10): 973 (Opinion).

Jensen MC. 1986. Agency costs of free cash flow, corporate finance, and takeovers. *American Economic Review* **76**(2): 323–329.

Kale P, Singh H. 2007. Building firm capabilities through learning: the role of the alliance learning process in alliance capability and firm-level alliance success. *Strategic Management Journal* **28**(10): 981–1000.

Kale P, Singh H, Perlmutter H. 2000. Learning and protection of proprietary assets in strategic alliances: building relational capital. *Strategic Management Journal*, March Special Issue **21**: 217–237.

Kim C, Mauer DC, Sherman AE. 1998. The determinants of corporate liquidity: theory and evidence. *Journal of Financial and Quantitative Analysis* **33**: 335–359.

Kogut B, Zander U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science* **3**: 383–397.

Koza MP, Lewin AY. 1998. The co-evolution of strategic alliances. *Organization Science* **9**(3): 255–264.

Koza MP, Lewin AY. 2000. Managing partnerships and strategic alliances: raising the odds of success. *European Management Journal* **18**(2): 146–151.

Lanjouw JO, Schankerman M. 2001. Characteristics of patent litigation: a window on competition. *Rand Journal of Economics* **32**(1): 129–151.

Laroia G, Krishnan S. 2005. Managing drug discovery alliances for success. *Research Technology Management* **48**(5): 42–50.

Larson A. 1992. Network dyads in entrepreneurial settings: a study of the governance of exchange relationships. *Administrative Science Quarterly* **37**(1): 76–104.

Lavie D, Rosenkopf L. 2006. Balancing exploration and exploitation in alliance formation. *Academy of Management Journal* **49**(4): 797–818.

Leland H, Pyle D. 1977. Informational asymmetries, financial structure, and financial intermediation. *Journal of Finance* **32**(2): 371–387.

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

Lerner J. 1994b. Venture capitalists and the decision to go public. *Journal of Financial Economics* **35**: 293–316.

Lerner J, Shane H, Tsai A. 2003. Do equity financing cycles matter? Evidence from biotechnology alliances. *Journal of Financial Economics* **67**: 411–446.

Levinthal DA, March JG. 1993. The myopia of learning. *Strategic Management Journal*, Winter Special Issue **14**: 95–112.

Mansfield E. 1968. *Industrial Research and Technological Innovation*. Norton: New York.

Mansfield E. 1986. Patents and innovation: an empirical study. *Management Science* **32**(2): 173–181.

March JG. 1991. Exploration and exploitation in organizational learning. *Organization Science* **2**(1): 71–87.

McGrath RG, Nerkar A. 2004. Real options reasoning and a new look at the R&D investment strategies of pharmaceutical firms. *Strategic Management Journal* **25**(1): 1–21.

Myers SC, Majluf NS. 1984. Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics* **13**: 187–221.

Nerkar A, Paruchuri S. 2005. Evolution of R&D capabilities: the role of knowledge networks within a firm. *Management Science* **51**(5): 771–785.

Okuno-Fujiwara M, Postlewaite A, Suzumura K. 1990. Strategic information revelation. *Review of Economic Studies* **57**: 25–47.

Opler T, Pinkowitz L, Stulz R, Williamson R. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* **52**: 3–46.

Papaioannou GJ, Strock E, Travlos NG. 1992. Ownership structure and corporate liquidity policy. *Managerial and Decision Economics* **13**: 315–322.

Podolny JM, Stuart TE, Hannan MT. 1996. Networks, knowledge and niches: competition in the worldwide semiconductor industry, 1984–1991. *American Journal of Sociology* **102**: 659–689.

Roberts K, Weitzman ML. 1981. Funding criteria for research, development, and exploration projects. *Econometrica* **49**: 1261–1287.

Robertson TS, Eliashberg J, Rymon T. 1995. New product announcement signals and incumbent reactions. *Journal of Marketing* **59**(3): 1–15.

Rothaermel FR. 2001. Incumbent' s advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal* June–July Special Issue **22**: 687–699.

Scellato G. 2007. Patents, firm size and financial constraints: an empirical analysis for a panel of Italian manufacturing firms. *Cambridge Journal of Economics* **31**: 55–76.

Schmookler J. 1966. *Invention and Economic Growth*. Harvard University Press: Cambridge, MA.

Schumpeter JA. 1934. *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Harvard University Press: Cambridge, MA.

Spilker B. 1994. *Multinational Pharmaceutical Companies* (2nd edn). Raven Press: New York.

Stephan PE. 1996. The economics of science. *Journal of Economic Literature* **34**: 1199–1235.

Stulz RM. 1990. Managerial discretion and optimal financing policies. *Journal of Financial Economics* **26**: 3–27.

Tong X, Frame JD. 1994. Measuring national technological performance with patent claims data. *Research Policy* **33**: 133–141.

Trajtenberg M. 1990. A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economics* **21**(1): 172–187.

USPTO. 2008. Handbook of Classification. available at http://www.uspto.gov/web/offices/opc/documents/handbook.pdf.

von Hippel E. 1994. 'Sticky information' and the locus of problem solving: implications for innovation. *Management Science* **40**(4): 429–439.

Wawro G. 2002. Estimating dynamic panel data models in political science. *Political Analysis* **10**: 25–48.