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EXPERIENCE EFFECTS AND COLLABORATIVE RETURNS IN R&D ALLIANCES

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Focusing on the link between prior alliance experience and firm benefits from R&D collaborations, this paper explores whether firms learn to manage their alliances. While prior experience should increase collaborative benefits from the current alliance, I expect these returns: (1) to be most beneficial when alliance activities are more uncertain; and (2) to diminish at high levels of experience. Results from a sample of 464 R&D alliances in the telecom equipment industry generally match these expectations. The positive benefits of prior experience in complex alliances suggest that a broader set of alliance management processes allows the firm to manage situations of ambiguity more readily. The lack of cumulative benefits from prior experience appears to be partly due to knowledge depreciating over time, since only recent experience has a positive impact on collaborative returns. Overall, these results provide empirical evidence of the effect of prior experience on collaborative benefits, both directly and conditionally on alliance characteristics, and have implications for learning to manage organizations more generally.

INTRODUCTION

> *The more alliances you do, the better you get at them. (Harbison and Pekar, 1998: 41)*

This statement, that firms become more proficient at alliance management with each additional alliance experience, is echoed in the popular press. Given the increasing use of alliances in recent years, effective management of such forms is important.[1] However, alliance management is difficult at best, as evidenced by the high rate of partner dissatisfaction and the high rate of alliance terminations in early years (e.g., Harrigan, 1985; Kogut, 1989; Bleeke and Ernst, 1993). Firms entering alliances face considerable coordination challenges. Uncertainty surrounding market changes, partner contributions, and collaborative outcomes makes effective management difficult. Further, since allying firms often have different expectations and place different values on alliance goals, fundamental conflicts of interest may arise and hinder benefits from collaboration. By developing alliance management skills, however, firms can coordinate more effectively with their partners and, ultimately, improve collaborative benefits.

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[1] Firms recognize the need for effective alliance management and now devote more resources to developing and maintaining alliance management skills. For example, a 1997 survey by Booz Allen & Hamilton finds that upwards of 50 percent of firms have dedicated alliance groups—management teams that pool alliance management skills and disseminate such experiential knowledge within the organization. As one manager interviewed noted, 'I think nearly every company is now recognizing that alliance management isn't something that just occurs, that it is a skill ... We need to make sure that we're the best partner, and so that is why we're aligning ourselves with what we think are some of the best practices to deliver value to ourselves and the partner' (Director of alliance management, *Fortune* 100 firm).

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Unfortunately, we still lack substantial evidence on how firms develop such skills. In this paper, I examine the extent to which firms learn to manage alliances from experience.

Prior literature on learning curves demonstrates that firms with greater experience enjoy advantages over competitors.[2] While the majority of this literature pertains to the effect of production experience on production cost, the effects of operating experience in service industries (e.g., Darr, Argote, and Epple 1995; Baum and Ingram, 1998), competitive experience (e.g., Barnett, Greve, and Park, 1994; Miller and Chen, 1994) and collaborative experience (e.g., Simonin and Helleloid, 1993; Anand and Khanna, 2000a) on various measures of performance have also been examined. Generally, as experience increases, a firm has more opportunities to make inferences about the effectiveness of various production or operating processes. Here, I extend this general logic to argue that firms learn to manage alliances as experience increases. This means that firms with greater alliance experience are likely more effective managers of current alliances than those firms with little or no such experience. Given that benefits from alliances depend crucially on the ability of allying firms to coordinate and manage alliance activities, I argue that as alliance management skill increases, collaborative benefits similarly increase.

Recent empirical work takes steps toward identifying whether prior experience is expected to improve alliance outcomes. Both Anand and Khanna (2000a) and Merchant and Schendel (2000) use event study analysis to examine whether prior experience leads to abnormal stock price returns on alliance announcement. Anand and Khanna (2000a) find that prior alliance experience is positively correlated with abnormal stock price returns on joint venture announcement, suggesting that firms learn to create more value as they accumulate experience with joint ventures.[3] Further, Anand and Khanna (2000a) find that the effect of prior experience on returns depends on the type of alliance activities—R&D, production, or marketing—and suggest that alliances with more ambiguous activities are more likely to benefit from prior experience. While this study demonstrates conditions under which alliance experience is expected to improve alliance success, we still require evidence as to whether firms actually reap more from their collaborations when they have prior alliance experience. By examining firm benefits from alliances, we can get a sense of whether the stock market's anticipation is correct. Further, we can tease out in more detail the types of alliances for which prior experience matters most and the limits to learning from prior experience (if any), at least in the context of R&D alliances.

Thus, I examine: (1) whether firms learn to manage R&D alliances by testing the relationship between prior experience and firm collaborative benefits; and, (2) if so, whether this effect differs according to alliance characteristics. Below, I argue that while there are positive benefits from prior experience (that is, firms appear to learn to manage alliances), firms realize diminishing marginal returns from each additional alliance experience. Success in managing alliances may lead firms to exploit their existing expertise and explore fewer new management techniques. As the requirements for success in alliances change over time, this exploitation at the expense of exploration can lead to reduced performance. Alternatively, alliance management expertise may depreciate over time, with either management turnover or the changing nature of collaboration in high-technology industries. I also argue that prior experience matters more for some alliances than for others. Where alliance activities are characterized by greater uncertainty, experience has a greater impact on collaborative benefits. Prior experience provides firms with a broader set of experiences to draw upon; these broader experiences are likely more important when firms are required to exercise judgment than in cases where decisions rely more on readily observable criteria. Of course, it is difficult to capture learning directly. We cannot measure, for example, the number of hours a firm spends managing each additional alliance, since firms do not report such information and alliances are not uniform such that inferences as to the number of hours spent can be made. Thus, similar to Baum and Ingram (1998), I infer learning by discrete experience and examine the benefits

[2] See, for example, Yelle (1979), Lieberman (1989), Dutton and Thomas (1984).

[3] These findings contrast with those found by Merchant and Schendel (2000), where no relationship between abnormal returns on alliance announcement and prior international alliance experience was found. Merchant and Schendel (2000), however, studied international joint ventures exclusively and it is likely that most firms in the sample had fairly extensive prior experience.

of learning as improvements in firm collaborative benefits.[4]

Using a sample of 464 R&D alliances in the telecommunications equipment industry, I test these arguments linking prior alliance experience with firm innovative performance. I find that prior alliance experience does increase collaborative benefits. However, firms do not seem to benefit from extensive experience—collaborative benefits are improved most with some experience, but extensive experience does not add to this effect. This lack of cumulative benefits from prior alliance experience appears to be partly due to the depreciation of knowledge over time, since only recent experience has a positive impact on collaborative returns.

I then test whether prior experience has a greater impact on collaborative benefits when alliances are more complex or have more uncertain outcomes. Using a constructed measure to identify the extent to which an alliance is characterized by greater complexity or uncertainty, I estimate the effect of prior experience on performance. I find that prior experience matters more for those alliances characterized by greater complexity or with more uncertain outcomes. This result suggests that firms develop judgment or other means of dealing with ambiguity via prior experience such that collaborative benefits are improved. These findings imply that managerial experience is, in fact, a firm capability that has important implications for performance.

In the paragraphs that follow, I review the literature linking experience with learning and performance in alliances. Hypotheses affecting firm collaborative outcomes, captured via firm patenting behavior post alliance, are developed on the basis of these arguments. I then describe the alliance and patent data used in this study to capture the link between experience and collaborative benefits. A description of measures and statistical methods used is followed by a discussion of results and implications.

LEARNING FROM EXPERIENCE

Firms learn by direct experience. The learning-by-doing, or experience-curve, literature demonstrates that cumulative production experience improves manufacturing productivity, primarily through cost reduction. As firms increase production experience, for example, they are better able to attribute outcomes to changes in inputs and processes. With this experience, firms can adopt better processes as they are discovered. In this sense, a firm's ability to learn is a function of its history of success and failure (Levitt and March, 1988; Radner, 1975). It follows that the richer the prior experience of the firm, the greater its exposure to various combinations of processes, inputs, and outcomes. Adaptation should follow, as, for example, firms remove redundant processes and find scale economies. It is this increased efficiency that is often referred to as 'learning.'

Extensive empirical research supports these arguments, showing that total production costs decrease with cumulative output.[5] For example, Lieberman (1984) finds that prices in the chemical industry drop with increased industry output and cumulative investment, rather than time per se, suggesting that firms learn with increased experience. Similarly, Argote, Beckman, and Epple (1990) find that the cost of manufacturing Liberty ships declined initially as production increased. While most of the learning research examines manufacturing outcomes, similar results have been found in other settings, such as service industries. For example, Darr *et al.* (1995) show that unit production costs in food franchises decline with increased experience. While estimates of learning rates differ by industries and across time (Dutton and Thomas, 1984; Dutton, Thomas, and Butler, 1984), the evidence that firms improve efficiency via direct experience is virtually indisputable.

While the learning curve literature has shown that firms improve production efficiency with increased experience, the same arguments can be

[4] This is a notion similar to 'survival enhancing learning' used by Baum and Ingram (1998). As Baum and Ingram note: 'our formal analysis is of the relationship between experience and failure. Therefore, we refer to the type of learning we study as "survival-enhancing learning", which we define as occurring when experience leads to a decrease in an organization's risk of failure. There are a number of intermediate processes that can account for survival enhancing learning, and our analysis is meant to point to their collective importance, not to determine the relative importance of any particular intermediate process' (Baum and Ingram, 1998: 996–997). Thus, here I examine how experience affects collaborative returns, where learning is one of the possible processes that could lead to positive experience effects.

[5] See Yelle (1979), Dutton and Thomas (1984), Levitt and March (1988), and Argote, Beckman, and Epple (1990) for more thorough reviews of this literature.

applied to understand the role of experience in the management of organizations more generally. Firms may be better able to manage certain types of activities, such as development of new divisions, changing product lines in response to environmental changes, and research aimed towards development of new products or processes, the more a firm engages in such activities. As with production outcomes, firms observe outcomes of management practices and selectively adopt new practices to improve performance. For example, in their study of the Manhattan hotel industry, Baum and Ingram (1998) find that hotel survival rates have a U-shaped relationship with the extent of prior operating experience. Baum and Ingram suggest that, with greater operating experience, hotels gain information on consumer preferences that allows the hotel to make changes to remain competitive. Other studies similarly examine the role of learning in managing organizations, suggesting that learning may improve performance in ways other than by decreasing production costs. For example, Haspeslagh and Jemison (1991) write of how to manage acquisitions, Chang (1995) discusses how to manage cross-border entry, and Harbison and Pekar (1998) discuss how to manage alliances more effectively. While these studies do not directly examine the effects of prior experience on the ability to manage organizations, they suggest that experiential learning influences organizational performance.

EXPERIENCE EFFECTS IN MANAGING ALLIANCES

Managing alliances is often difficult due to the very nature of alliances: two or more separate firms, often with competing interests and expectations, working together to achieve a particular outcome. Allying firms frequently have different managerial styles and practices, making communication and coordination more challenging. Activities that are often difficult to manage within a firm are complicated by the need to coordinate such challenging activities across firm boundaries. For example, when making strategic-level decisions regarding alliance activities, allying firms not only need to build consensus within their own organizations, but also build consensus in their partner's organization. Firms also have difficulty observing the activities of their partners directly. When allying firms do not have fully aligned interests (for example, where partners compete in the same lines of business), the inability to observe partner actions makes conflicts more likely.

Survey-based evidence reflects these difficulties in alliance management: over 40 percent of partners report that they are very dissatisfied with the results of their collaborations (Bleeke and Ernst, 1993). Other estimates find similar rates of partner dissatisfaction (Harrigan, 1985; Anderson Consulting, 1999).[6] Larger-scale empirical studies of alliance terminations also suggest that alliances are difficult to manage: Kogut finds a significant number of joint venture terminations at an early stage, suggesting that 'many of these terminations are a result of business failure or a fundamental instability in governance,' (Kogut, 1989: 184). While we do not have conclusive evidence of the reasons for these high rates of dissatisfaction and early termination, it appears that the difficulties inherent in managing interfirm collaboration are at least partially responsible. In a recent survey, allying firms state that shifts in partners' objectives and expectations, waning managerial attention, and clashes in corporate culture are at least partly responsible for the majority of alliance failures (Pillemer and Racioppo, 1999).

There are several examples of how participation in prior alliances may improve outcomes from later alliances. With each alliance experience, firms can better assess the appropriate contract structure for their collaborative activities. Choice of contract structure is important, since appropriate choice of contract structure has been linked to performance in multiple contexts, including alliances.[7] The ability to assess alliance performance on an ongoing basis has also been suggested as an important determinant of alliance success (Harbison and Pekar, 1998). Given that collaboration requires coordination at some level, communication of strategic level decisions is important—allying firms must be able to align their respective strategies for the alliance activities at regular intervals

[6] Harrigan (1985) finds that approximately 50 percent of alliances 'fail.' A study by Anderson Consulting finds that over 61 percent of alliances fail or do not fulfill partner expectations (Anderson Consulting, 1999).

[7] See, for example, Sampson (2004b), who finds that appropriate selection of contract structure improves performance in R&D alliances. Macher (2004) shows similar results, in the context of semiconductor manufacturing—the appropriate choice of make or buy improves performance substantially over the inappropriate choice.

to avoid veering off course or disruptive conflicts. Regular communication may also ease clashes in corporate culture that may threaten success.

Without an awareness of the unique incentive and management problems presented in alliances and means to respond to these problems, firms may not be able to benefit from collaboration. Either allying firms may not be able to effectively collaborate or firms may not be able to translate the collaboration into benefits for themselves. With prior experience, however, firms have the opportunity to observe what managerial practices work and what do not. Thus, via prior alliance experience, allying firms can develop means to assess alliance performance, judge how best to communicate with partners, and develop other metrics that provide guidance for other decisions such as alliance contract structure.

Fundamentally, repeated participation in alliances exposes firms to variation in alliance management practices and outcomes. A firm develops a 'broad repertoire of experiences' (Anand and Khanna, 2000a: 298), which allows the firm to make inferences about the likely outcomes of various alliance management practices. Thus, more extensive alliance experience allows firms to identify effective processes for exchanging information and technology with their partners as well as processes to manage complex activities with uncertain outcomes. Via prior experience, firms may also gain insights on how to disseminate information gained from their collaborations within the firm, thus improving overall collaborative outcomes. Therefore, it follows that the more extensive a firm's prior alliance experience, the greater the firm's ability to select appropriate management processes for current and future alliances. Collaborative benefits are improved as a result.

These arguments suggest that the greater a firm's alliance experience, the greater the collaborative benefits from a current or future alliance. However, there may be limits to the positive benefits of accumulated alliance experience. Learning often leads to adoption of specific processes that are perceived to improve outcomes. Given that these processes are perceived to improve outcomes, firms will use the processes more frequently. Where the frequent use of these processes precludes experimentation with new, possibly better, processes, a firm may experience stagnated or even reduced collaborative benefits. There is a substitution of exploitation of existing practices for exploration; learning and imitation of prior experiences may inhibit experimentation that could improve collaborative benefits (March 1991: 73).[8] Recent empirical evidence finds that the value of experience decays over time, suggesting that the benefits from such experience are likely not cumulative over time (Baum and Ingram, 1998; Darr *et al*., 1995; Argote *et al*., 1990). Firms may, for example, forgo adoption of new information transfer processes and alliance organizational forms where some success has been realized with current processes and forms.[9] As Baum and Ingram (1998: 998) note: 'Exploitation can become harmful, however, if the criteria for organizational success and survival change *after* the organization has learned' (emphasis in original).

Consequently, there is a tension between the positive effect of accumulated alliance experience and the inertia that may result from such prior experience. This implies that there are decreasing marginal returns to alliance experience. Prior alliance experience should, via a process of selective adaptation, improve alliance outcomes. However, with more extensive alliance experience, firms may lock into currently productive routines, causing inertia and the inability to adopt new, more productive processes. This logic leads to my first hypothesis:

Hypothesis 1: There are decreasing marginal returns to prior alliance experience. Firm collaborative benefits initially increase with the firm's prior alliance experience, but this rate of increase diminishes at higher levels of experience.

The above arguments suggest that prior alliance experience improves outcomes in future alliances of any kind. There are reasons to expect that prior experience matters more for some alliances than for others. Given that prior alliance experience provides a broader repertoire of experiences to draw

[8] In other words, the firm is experiencing a 'competency trap' (Levitt and March, 1988).

[9] Maladaptation is also possible; firms may make incorrect inferences about what processes have led to observed outcomes. Further, the causality of events is often difficult to identify and categorizing outcomes as positive or negative is not always straightforward (Levitt and March, 1988). As such, increased experience may not always lead to improve outcomes. However, there is no reason to believe that this maladaptation is systematic or correlated with the type or extent of alliance experience. For the purposes of this study, such mistakes are assumed to be random occurrences.

on when making inferences about the likely outcomes of certain actions, prior alliance experience may provide enhanced judgment or a better ability to manage uncertainty or ambiguity. As such, prior experience should matter more for alliances that require more advanced judgment, such as alliances with idiosyncratic activities, rather than those alliances where ongoing performance can be easily verified. Anand and Khanna similarly argue that the effect of prior experience (or learning) on alliance success is conditional on 'the extent of ambiguity or complexity of contingencies facing alliance partners' (Anand and Khanna, 2000a: 299).

Generally, managerial experience has the greatest potential to affect performance in situations that are characterized by greater complexity and/or where outcomes are highly idiosyncratic or uncertain. Activities with greater complexity demand a greater share of managerial attention and skill than those activities with relatively simple processes. For example, firms have less guidance on how to evaluate performance of alliance activities when partner contributions and outcomes cannot be well specified in advance. In these situations where outcomes are highly idiosyncratic or uncertain, experience likely matters more, since experience provides firms with a set of tools or metrics for analyzing ambiguous situations.[10]

Via prior experience with such alliances, firms may observe practices that improve outcomes in these alliances such as means to track progress, estimate performance, and manage the ongoing relationship with the partner(s). Thus, the broader the firm's repertoire of management processes for alliances, the better the ability of the firm to manage alliances with uncertain and/or complex activities and, consequently, the better the collaborative outcomes from the current alliance. This logic leads to my second hypothesis:

Hypothesis 2: Prior alliance experience has a greater positive effect on firm collaborative benefits when the alliance activities are more uncertain or complex than where alliance activities are less uncertain or complex.

[10] In his extensive study of decision-making under conditions of stress and high uncertainty, Klein (1998) argues that experience provides individuals with a range of tools that lead to optimal choices.

EMPIRICAL ANALYSIS

Empirical design

To test the relationship between prior alliance experience and alliance outcomes, I measure firm innovation (post alliance commencement) as a function of prior alliance experience and relevant controls. I expect that as a firm's alliance experience rises, innovative performance rises but at a decreasing rate. I use firm innovation as the outcome measure, since the context I use to examine the relationship between experience and performance is collaborative R&D. Innovation or, here, patenting activity, is more directly linked to R&D than financial performance measures, such as return on assets.

Firm innovative performance is an appropriate measure of alliance outcomes for several reasons. Collaborations form an important part of a firm's R&D strategy in many industries and, as such, measures of alliance outcomes should include the impact of collaboration on the partner firms. Failing to account for the contribution of an alliance to firm performance may ignore the most meaningful measure of collaborative effectiveness. Further, since alliance outcomes are often not directly measurable, we can only measure alliance success via the partner firms.[11]

To examine whether prior experience matters more for alliances with activities that are relatively complex and/or uncertain, I split the sample according to the complexity or uncertainty of alliance activities and estimate the impact of alliance experience on collaborative outcomes. By comparing estimates between the two samples, we can get an idea of whether alliance experience does in fact matter more for alliances where managerial judgment is hypothesized to be more important for performance. To identify which alliances have more uncertain or complex activities, I calculate a composite measure of alliance characteristics.

[11] Of course, capturing the contribution of an alliance to firm performance presents empirical difficulties. Since we cannot identify the intellectual origins of a patent (innovation), we must rely on statistical techniques to estimate the contribution of an alliance to firm innovative performance. I rely on the inclusion of strong firm controls, capturing the research productivity of that firm, to tease out innovation or patents due to firm efforts. We can then observe whether alliance characteristics, such as experience, affect firm innovative performance via the parameter estimates of included alliance variables. If there is no effect of an alliance on firm innovation, we should observe significant coefficients only for the firm controls, not the alliance variables.

This composite measure is the estimated probability that allying firms choose an equity joint venture (versus a more contractual form) for alliance organizational form, given alliance characteristics. The probability of choosing an equity joint venture is a signal of the underlying complexity of alliance activities.

Equity joint ventures relieve firms from fully specifying alliance activities in a contract and provide formal mechanisms for joint decision making and dispute resolution. Equity joint ventures, however, are generally more costly to set up and impose bureaucratic costs on the alliance, in the form of slowing and politicizing the decision-making process as well as dampening incentives of individual actors (Pisano, 1989; Oxley, 1997). Because of these attributes, allying firms generally choose an equity joint venture for their alliance activities when these activities are complex. Much recent empirical evidence confirms this general hypothesis, finding that equity joint ventures are generally chosen when the alliance has more than two partner firms involved, broad R&D activities, activities in addition to R&D activities, and greater technological differences between partner firms (e.g., Oxley, 1997; Pisano, 1989; Sampson, 2004b). In this sense, the probability of selecting an equity joint venture captures the degree of uncertainty or complexity of alliance activities. With this probability, we can identify alliances that have similar characteristics across a range of identified dimensions. As such, we can then compare alliances across multiple dimensions in order to examine whether the effects of learning, or prior experience, on firm collaborative benefits differ according to alliance characteristics. More information on the use of this probability estimate is set out in the Appendix.

Data and sample description

For these tests, I constructed a dataset containing information on alliance and patenting activity of firms in the telecom equipment industry.[12] This industry is appropriate for the study of R&D alliances and the impact of prior alliance experience on outcomes for several reasons. First, firms frequently collaborate in R&D in the telecom equipment industry in response to rapidly changing technology and the increase in the development costs.[13] R&D alliances represent one way firms can spread this cost of technological development, gain access to new capabilities, and speed new technology adoptions. Second, my dependent variable, citation-weighted patents (described below), is most appropriate in industries where patents are an important means of intellectual property protection. Levin *et al.* (1987) find that firms in the telecom equipment industry cite patents as an important mechanism for appropriating the returns to innovation.

The source of alliance data is the Securities Database Corporation (SDC) Database on Joint Ventures and Alliances. Information in this database covers all types of alliances from 1988 onwards and is compiled from publicly available sources, including SEC filings, industry and trade journals, and news reports. Coverage of alliances formed after 1988, while more comprehensive than pre 1988, is still incomplete, since firms are not required to report alliance activities. Nevertheless, the dataset is one of the most comprehensive sources of alliance information available and is one of the only sources available for large-scale empirical studies on alliances. Several recent studies have used these data, including Anand and Khanna (2000a, 2000b) and Sampson (2004a).

My alliance sample consists of all R&D alliances for firms in the telecom equipment industry commencing in the years 1991–93 inclusive. This time period allows more comprehensive alliance samples than earlier time periods but still allows sufficient time to track post-alliance patents.[14] Each alliance involves R&D activities either exclusively or in addition to marketing, production and/or supply activities. Based on these selection criteria, the sample includes 464 R&D alliances involving 487 firms across 34 nations. Most of the sample firms are from the United States (60%), with the remainder primarily from Japan (12%) and Europe (13%). Both same nation alliances (48%), where all partner firms are headquartered in the same nation, and international alliances (52%), where all partners are not headquartered in the same nation, are included the sample.

[12] The telecom equipment industry refers to those firms participating in SIC classes 3661, 3663, and 3669.

[13] See, for example, *The Economist* (1997), and Pisano, Russo, and Teece (1988).

[14] Note that for patents issued during the years 1975–97, 81 percent were issued within 2 years of application, while 96 percent were issued within 3 years of application.

I combine these alliance data with patent data from the Micropatent database, which contains information on all U.S. patents granted since 1975, including assignee name, patent technological classification, and inventor name. From this information, I construct a firm's patent portfolio. Because I am interested in testing the impact of prior alliance experience on a firm's innovative performance attributable to later alliances, I capture patents for the firm's entire corporate structure rather than a specific subsidiary. Since patents are often assigned to the ultimate parent firm and not the single subsidiary where the innovation took place, capturing the entire firm- or corporate-level patent portfolio is particularly important. For example, Sampson (2004b) finds that 73 percent of patents are assigned to the ultimate parent firm and 27 percent are assigned to various levels of subsidiaries within the firm. Thus, to avoid a noisy measure of firm innovative performance, I construct a patent portfolio for firms based on patents assigned to the parent firm as well as all of its subsidiaries. I first used the *Directory of Corporate Affiliations* to identify all of a firm's subsidiaries. I then drew all patents from the Micropatent database assigned to these parents or their subsidiaries and aggregated the identified patents at the corporate level.[15]

Measures

Dependent variable

Firm innovative performance (PATENT). I measure firm innovative performance via citation-weighted, firm patenting in a 4-year, post-alliance window. For example, if an alliance commences in 1991, PATENT is the sum of citation-weighted patents applied for 1992–95, inclusive.[16] Patents are strongly correlated with new products (Comanor and Scherer, 1969), literature-based invention counts (Basberg, 1982), and non-patentable innovations (Patel and Pavitt, 1997). As such, patents are reasonably reliable indicators of innovative performance and are generally better measures of the output of R&D activities than R&D spending (Comanor and Scherer, 1969; Griliches, 1990).

Since simple patent counts do not accurately capture the value of the underlying innovation (Griliches, 1990), I assign a weight to each patent using citations made by later patents. When a patent is granted, the inventor (and/or patent examiner) notes all of the previous patents that the granted patent is based upon. These 'citations' of previous patents identify the technological lineage of the invention and effectively define the property rights granted by the patent (Jaffe and Trajtenberg, 1997). Empirical evidence shows a strong correlation between the *ex post* citations of the patent and the estimated value of the underlying invention (e.g., Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 1998). As such, citation weighting provides a less noisy measure of innovation than simple patent counts. I use the application date, since this date is the earliest point at which we can identify new firm technology.

Focal independent variable

Prior alliance experience (EXPERIENCE). I measure prior alliance experience as a count of alliances that a firm has been involved in from 1985 up to, but not including, the year of the focal alliance. These alliances can be of any type, such as marketing, manufacturing, or supply. I measure experience by all types of prior alliance experience, since I argue that firms learn to manage the coordination difficulties inherent in R&D alliances with any type of prior alliance experience, rather than just prior R&D alliance experience. With any type of alliance, firms learn how to coordinate across organizational boundaries, select appropriate contract structures, evaluate performance and manage differences in corporate cultures. Coordination across

[15] Ideally, we would capture only those patents that are clearly linked to each alliance. However, linking patents with specific collaborations poses a serious challenge, given the difficulty in tracing a patent's intellectual origin. One alternative to the approach used here is to categorize patents as related or unrelated to an alliance based on the alliance activities. However, such a classification is highly subjective and inevitably arbitrary. As Hall, Jaffe, and Trajtenberg (2001: 13) note with respect to assigning patents to aggregate technology categories, an issue analogous to the assignment of patents to an alliance: 'there is always an element of arbitrariness in devising an aggregation system and in assigning the patent classes into the various technological categories, and there is no guarantee that the resulting classification is "right", or adequate for most uses.' While each approach has its limitations, here I rely on strong firm controls and alliance variables to empirically tease out the firm vs. alliance effects, rather than attempting to identify specific patents attributable to specific alliances.

[16] I begin with a 1-year lag between alliance commencement and firm patenting, since research shows a contemporaneous relationship between R&D efforts and patenting (e.g., Hausman *et al.*, 1984).

firm boundaries is always challenging and, therefore, skills gained in improving this coordination likely are gained from any type of alliance.[17] To take the hypothesized non-linear relationship into account, I take the natural log of this count as the independent variable. Several other constructions of this variable are used in robustness checks and are described in more detail below.

Control variables

It is possible that firms with greater experience are actually more capable firms in R&D. As such, prior experience may be capturing this capability rather than alliance managerial competence. This is precisely the rationale for including several controls such as prior firm patenting to control for firm R&D competence. By using these controls, we can tease out the effects of prior experience and have some confidence that any discovered relationships are not purely attributable to firm R&D competence, but are in fact capturing alliance managerial competence.

Pre-alliance firm and partner patents (FIRM PATENT & PARTNER PATENT). To control for factors other than prior alliance experience that may influence firm innovation (or patenting) rates, I include variables capturing inputs into the firm R&D process. To capture the firm's R&D efforts, I include a count of pre-alliance firm patenting. While firm patenting is used as a measure of the output of a firm's R&D efforts, firm patenting is also used to measure inputs into the R&D process. Prior patents capture a firm's technological capabilities generally (Patel and Pavitt, 1997), technological acquisitions, R&D spending, and a firm's propensity to patent (Trajtenberg, 1990). Thus, for each firm, I capture pre-alliance firm patenting via a count of firm patents in a pre-alliance, 4-year window. Because inputs into the alliance R&D process include not only a firm's inputs but its partner's as well, I include a similar measure for partner firms: a 4-year, pre-alliance count of partner firm patents. While it is possible to weigh pre-alliance patent counts by citations, Trajtenberg (1990) finds that unweighted patent counts are more highly correlated with R&D spending and other R&D inputs than citation-weighted patent counts and, as such, are better measures of R&D inputs.[18,19]

Diversity of technological capabilities (TECHNOLOGICAL DIVERSITY). In addition to accounting for partner firm technological capabilities via a pre-alliance patent count, it may also be necessary to control for the degree to which a firm's capabilities differs from its partner's. Sampson (2000) finds that collaborative benefits increase as partner capabilities become more dissimilar, suggesting that partners then have more to learn from each other. As such, I include a measure of the diversity of partner capabilities based on the distribution of each firm's patents across patent classifications. Following Jaffe (1986), I first create a multidimensional vector of firm patents across technological classifications, year by year: $F_i = (F_i^1 \cdots F_i^s)$, where F_i^s represents the number of patents assigned to partner firm i in patent class s. Diversity of partner firm capabilities is then[20]

$$\text{TECHNOLOGICAL DIVERSITY} = 1 - \frac{F_i F_j'}{\sqrt{(F_i F_i')(F_j F_j')}}$$

where $i \neq j$. This measure varies from zero to one; a value of one indicates the greatest possible diversity between partners.

While we might expect collaborative benefits to increase with technological diversity, since more new combinations or innovations are possible as diversity increases, this relationship may not be monotonic. Using absorptive capacity arguments, firms require some technological capabilities in common to use those not in common. This implies that higher levels of technological diversity may

[17] As a robustness check, I also estimated Tables 2 and 3 using a measure of experience that captures prior R&D alliances only (excluding manufacturing, marketing and other non-R&D alliances). These results are substantively similar to those reported in Tables 2 and 3 and are available from the author on request.

[18] Using various time lags between R&D spending and patent counts, Trajtenberg finds that the correlation between R&D spending and patents ranges from 0.831 to 0.933; this correlation is highly significant at all lags ($p \leq 0.0008$ for all lags).

[19] In the empirical work below, I report results using simple patent counts for a firm's and its partner's prior alliance patents (i.e., no citation weighting). However, results are substantially similar (albeit statistically less significant) with citation-weighted versions of these measures.

[20] This measure calculates diversity as between a pair of firms. For alliances involving more than two firms, I calculate this measure for every combinatorial pair of firms in the alliance and take the average of these measures.

actually dampen outputs since firms cannot utilize the technological capabilities of their partners. As such, I include the square of TECHNOLOGICAL DIVERSITY to account for this suggested non-monotonic relationship.

Alliance scope (SCOPE(Narrow) and SCOPE (Broad)). Collaborative R&D projects range in breadth, from very narrow projects (e.g., to develop hardware specific applications of software) to very broad (e.g., to develop the next generation of integrated circuits). As such, we expect alliance outcomes to vary according to this project breadth. Using the synopses of alliance activity from the SDC database, I construct three dummy variables to capture narrow-, intermediate-, and broad-alliance R&D activities. These three categories were developed in concert with the R&D manager of a U.S. multinational firm. Narrow scope, SCOPE(Narrow), identifies those alliances focused on development of new products based closely on existing technology. Activities that go beyond customization of existing products to a new user but fall short of developing next-generation products are categorized as intermediate: SCOPE(Intermediate). The broadest collaborative R&D projects are those intended to produce 'next-generation' products and are identified as alliances with broad scope: SCOPE(Broad). Since alliances with intermediate breadth are the most common, I omit SCOPE(Intermediate) from the empirical analyses.[21]

Multilateral alliances (MULTILATERAL). Collaborative returns from alliances with more than two partner firms, or multilateral alliances, may differ from bilateral alliance returns. Multilateral alliances may signal a larger alliance, with greater capabilities. As such, we might expect returns from such alliances to be greater. To control for this possible effect, I include a dummy variable, MULTILATERAL, which equals one if the number of partner firms exceeds two.

International alliances (INTERNATIONAL). When partner firms are headquartered in different nations, collaborative R&D activities may be more difficult to coordinate. Since less effective coordination may reduce collaborative benefits, I include a dummy, INTERNATIONAL, to indicate whether the alliance is international. INTERNATIONAL equals one if the alliance is international, zero otherwise.

Other concurrent alliance(s) (OTHER ALLIANCE). Firm patenting rates vary not only by their R&D efforts and current alliance activity, but possibly also by the existence of other concurrent alliances. To control for possible differences in patenting rates between firms with only one ongoing alliance and those with multiple ongoing alliances, I construct a dummy variable, OTHER ALLIANCE, which equals one if a firm is involved in more than one alliance during the sample period (1991–93), zero otherwise.

Time of alliance commencement (YEAR(1992) and YEAR(1993)). Two year dummies, YEAR(1992) and YEAR(1993), are also included, since I expect *ex post* patenting rates for later year alliances to be less than early year alliances. Our ability to observe patents applied for in later years, such as 1996 and 1997, is limited because the patent data runs only until 1997. While 81 percent of patents are granted within 2 years of application, later years of patent data are required to comprehensively count the patents applied for in these later years. I expect both dummies to be negative, reflecting this data truncation.

Statistical method

As described above, the dependent variable is a count of citation-weighted patents. Count-dependent variables are necessarily non-negative, integer values. Patent counts also display other consistent characteristics, namely a high frequency of zero and small integer values. To account for these characteristics in the dependent variable, I use a negative binomial specification. Zero and small counts are naturally incorporated into the model (Hausman *et al.*, 1984). The negative binomial model is

$$\Pr[PATENT = p] = \frac{e^{-\lambda}\lambda^{p}}{p!} \quad (1)$$

[21] The variables were coded by two independent coders, with greater than 70 percent concordance between coders. More detail on the SCOPE coding scheme is available from the author on request.

where λ is $e^{\beta' X+\varepsilon}$, X is a vector of independent variables and β is a vector of parameters.[22]

Note that not all errors are independent in this model. Since I include an observation for each alliance a firm is involved in, a firm may have multiple observations representing the firm's participation in multiple alliances. To correct this lack of independence between observations involving the same firm, I use a technique by Huber (1967) to correct the standard errors. If a firm is involved in multiple alliances during the sample period, I sum the likelihood scores for that firm to create a 'super observation' (Huber, 1967). It is this single, super observation that I use to calculate standard errors.[23] Parameter estimates do not require correction, since maximum likelihood estimates are unbiased and consistent even when the assumption of independence is violated (Greene, 1990).

Empirical results

The sample consists of 464 R&D alliances, involving 487 firms in the telecom equipment industry. Sixty-nine percent of these firms are involved in only one R&D alliance during the sample period (1991–93). However, 13 percent of sampled firms are involved in two alliances, 6.5 percent are involved in three alliances, and 11.5 percent are involved in anywhere from four to sixty-two alliances during the period. To account for these various alliances, I create a separate observation for each alliance a firm is involved in, leading to a sample of 1005 observations. Table 1 presents descriptive statistics for all variables.

To test whether firms learn to manage alliances with greater experience, I estimate firm patenting as a function of prior alliance participation along with relevant controls. Results from this estimation are set out in Table 2.[24]

Table 2(column 1) captures prior alliance experience via a logged count of prior alliances that the firm has participated in. From this estimation, we see that the count of prior alliances has a positive and significant effect on firm patenting performance. To get an idea of the impact of, for example, increasing prior alliance experience by one, I calculate a firm's expected (citation-weighted) patents at different levels of alliance experience. For this calculation, I first take the estimates from Table 2(column 1) and evaluate these estimates at the median values of the independent variables. Using a negative binomial model, $E[\mathit{PATENT}] = \lambda = e^{\beta' X}$, where X represents the independent variables and controls used in Table 2(column 1) (Cameron and Trivedi, 1986: 33). After calculating $E[\mathit{PATENT}]$, I vary the count of prior alliances for a firm and measure the impact on $E[\mathit{PATENT}]$. An increase in prior experience by a single alliance increases post-alliance (citation-weighted) patenting by 3.87. Although this effect is statistically significant, given that the mean and median values of $E[\mathit{PATENT}]$ are 461 and 13, respectively, this increase in performance does not appear to be substantively significant.

To relax the assumption of a logarithmic relationship between prior experience and firm patenting, I then estimate the relationship between experience and performance using several alternative variable constructions. In the remaining columns in Table 2, I estimate the effect of prior experience on collaborative benefits using a count of prior alliances (column 2), a dummy indicating whether a firm has prior alliance experience (column 3), several dummies indicating the extent of prior experience (column 4), and a piecewise analysis of the extent of prior experience (column 5). Results from all columns also show a positive and significant effect of prior experience on collaborative benefits.

Results in column (2) show that, as the count of a firm's prior alliances increases, collaborative benefits from the current alliance also increase. Of course, measuring prior experience via a count of prior alliances makes a strong assumption. A count measure effectively assumes that the difference, for example, between no experience

[22] λ follows a gamma distribution with parameters (γ, δ), where $\gamma = e^{\beta' X}$ and δ is common across observations. This treatment controls for unobserved heterogeneity in λ by adding an error term (i.e., $\lambda = e^{\beta' X+\varepsilon}$).

[23] Thus, the standard variance estimate for maximum likelihood estimation is: $\hat{V} = \hat{\mathrm{V}}(\sum_{\mathrm{i}=1}^{\mathrm{n}} u_i^{j\prime} u_i^j)\hat{\mathrm{V}}$, where: $\hat{\mathrm{V}} = (\frac{\partial^2 \ln L}{\partial \beta^2})^{-1}$, and $u_i^j = \sum_{i\in j} u_i = \sum_{i \in j} \frac{\partial \ln L_i}{\partial \beta}$. Here, u_i is the contribution of the ith observation to the score of firm j, and u_i^j is the contribution of firm j to the overall likelihood function.

[24] Beyond the Wald chi-square measure for goodness of fit, I also ran several likelihood ratio tests to capture whether the models with measures of experience included in Table 2 fit the data significantly better than models without experience measures. In all cases but one, models with experience fit the data significantly better than models without such measures included. For Table 2, specification (2), the likelihood ratio test was significant at the 0.13 level, just outside the conventional significance levels.

Table 1. Descriptive statistics

Correlations (correlation, significance)	1	2	3	4	5	6	7	8	9	10	11	12	13
1 PATENT	1.000												
2 EXPERIENCE: COUNT	0.335	1.000											
	0.000												
3 FIRM PATENT	0.833	0.337	1.000										
	0.000	0.000											
4 PARTNER PATENT	0.070	−0.002	0.047	1.000									
	0.027	0.946	0.135										
5 TECHNOLOGICAL DIVERSITY	−0.379	−0.149	−0.365	−0.254	1.000								
	0.000	0.000	0.000	0.000									
6 TECHNOLOGICAL DIVERSITY (squared)	−0.380	−0.153	−0.358	−0.294	0.992	1.000							
	0.000	0.000	0.000	0.000	0.000								
7 SCOPE (Narrow)	−0.032	0.012	−0.038	−0.023	0.076	0.078	1.000						
	0.311	0.695	0.228	0.468	0.016	0.013							
8 SCOPE (Broad)	−0.018	−0.046	0.043	0.097	−0.077	−0.079	−0.279	1.000					
	0.562	0.147	0.177	0.002	0.014	0.013	0.000						
9 MULTILATERAL	0.031	−0.005	0.020	0.496	−0.070	−0.099	0.013	0.122	1.000				
	0.334	0.885	0.537	0.000	0.028	0.002	0.679	0.000					
10 INTERNATIONAL	0.048	0.005	0.099	0.137	0.012	0.004	0.076	−0.082	0.207	1.000			
	0.128	0.882	0.002	0.000	0.694	0.902	0.016	0.009	0.000				
11 OTHER ALLIANCE	0.261	0.423	0.253	0.048	−0.203	−0.211	0.014	−0.100	0.069	0.035	1.000		
	0.000	0.000	0.000	0.127	0.000	0.000	0.657	0.002	0.029	0.272			
12 YEAR(1992)	0.150	−0.001	0.149	0.006	−0.111	−0.108	0.009	0.002	−0.008	−0.022	0.080	1.000	
	0.000	0.979	0.000	0.853	0.000	0.001	0.771	0.947	0.811	0.479	0.011		
13 YEAR(1993)	−0.198	0.094	−0.086	0.068	0.095	0.097	−0.113	0.055	0.047	0.041	−0.080	−0.683	1.000
	0.000	0.003	0.006	0.032	0.003	0.002	0.000	0.079	0.141	0.198	0.011	0.000	
Mean	461.68	4.90	357.95	1275.84	0.94	0.90	0.35	0.12	0.34	0.54	0.68	0.56	0.27
Median	13.00	1.00	5.00	218.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00	1.00	0.00
Minimum	0.00	0.00	0.00	0.00	0.13	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	6420.00	47.00	4822.00	7887.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
S.D.	974.73	7.73	771.76	1780.33	0.14	0.21	0.48	0.33	0.47	0.50	0.47	0.50	0.44
$n = 1005$													

Table 2. Prior experience and performance

	(1)	(2)	(3)	(4)	(5)
INTERCEPT	0.921	0.848	0.965	0.873	0.930
	1.135	1.098	1.209	1.194	1.216
LOG(EXPERIENCE)	0.217***				
	0.106				
EXPERIENCE: COUNT		0.017*			
		0.011			
EXPERIENCE > 0 (dummy)			0.634***		
			0.245		
EXPERIENCE: 1–5 (dummy)				0.525***	
				0.240	
EXPERIENCE: 6–10 (dummy)				0.613**	
				0.356	
EXPERIENCE:>10 (dummy)				0.560**	
				0.317	
EXPERIENCE > 0 (dummy)					0.601***
					0.255
EXPERIENCE > 5 (dummy)					0.095
					0.312
EXPERIENCE > 10 (dummy)					−0.030
					0.327
FIRM PATENT	0.002***	0.002***	0.002***	0.002***	0.002***
	0.000	0.000	0.000	0.000	0.000
PARTNER PATENT	0.000	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000
TECHNOLOGICAL DIVERSITY	13.708***	13.851***	13.207***	13.469***	13.403***
	3.449	3.378	3.652	3.545	3.582
TECHNOLOGICAL DIVERSITY^2	−11.027***	−11.079***	−10.665***	−10.829***	−10.808***
	2.444	2.412	2.559	2.481	2.497
SCOPE(Narrow)	−0.242**	−0.223*	−0.298***	−0.276**	−0.298***
	0.146	0.145	0.143	0.144	0.143
SCOPE(Broad)	−0.333**	−0.330**	−0.392***	−0.380***	−0.384***
	0.194	0.192	0.188	0.193	0.193
MULTILATERAL	0.108	0.128	0.133	0.109	0.124
	0.183	0.181	0.182	0.182	0.181
INTERNATIONAL	−0.025	−0.011	0.015	0.011	0.004
	0.190	0.193	0.188	0.188	0.186
OTHER ALLIANCE	0.900***	1.086***	0.768***	0.845***	0.763***
	0.256	0.249	0.252	0.252	0.255
YEAR(1992)	−0.427***	−0.433***	−0.415***	−0.419***	−0.420***
	0.212	0.211	0.205	0.207	0.212
YEAR(1993)	−1.226***	−1.214***	−1.196***	−1.167***	−1.209***
	0.232	0.228	0.219	0.227	0.239
n	1005	1005	1005	1005	1005
Wald chi-square	220.7	229.6***	229.7***	233.3***	237.0
d.f.	12	12	12	14	14

Negative binomial estimation.
Dependent variable is citation-weighted patents issued to each firm in a post-alliance period.
Positive coefficients indicate increased patent output.
Significant at * 10%, ** 5%, and *** 1% level for one-tailed tests.
Standard errors below coefficients.

and one prior alliance is the same as the difference between seven prior alliances and eight prior alliances. The fact that firms may not benefit substantially from additional alliance experience once they have participated in several prior alliances may dampen the estimated coefficient on prior experience. To relax this assumption and estimate the effect of simply having prior experience versus having none, I estimate $E[PATENT]$ as a function of prior experience captured as a dummy variable. EXPERIENCE > 0 equals one if a firm has any prior alliance experience and zero if not. These results are reported in Table 2, column (3). Prior experience significantly increases firm performance in a current alliance. This effect is not only statistically significant, but substantively significant as well; prior experience increases firm patenting by 43 (i.e., 43 'WPC'), an increase of 88 percent over patenting performance with no experience.[25] This result suggests that it is the *existence* rather than the *extent* of prior experience that affects a firm's ability to benefit from current alliance activity. Firms may learn the most from managing a single alliance; additional experiences may add very little relative to the first experience.

To further investigate this relationship, I measure prior experience via three dummy variables capturing the extent of experience. EXPERIENCE: 1–5 is one when a firm has participated in at least one but fewer than six alliances, zero otherwise. Similarly, EXPERIENCE:6–10 is one when a firm has participated in anywhere from six to 10 prior alliances and EXPERIENCE :> 10 is one when a firm has participated in more than 10 prior alliances, zero otherwise. The results using these new measures are set out in Table 2(column 4). All three estimates are positive and significantly different from zero. Consistent with the results above, having prior alliance experience improves a firm's ability to benefit from a current alliance. Having participated in from one to five prior alliances improves firm collaborative benefits by 36 WPC, an increase of 70 percent over collaborative benefits with no prior experience. Similarly, a firm participating in six to 10 prior alliances and more than 10 prior alliances increases its patenting performance by 44 WPC and 39 WPC, respectively, over its performance with no such prior experience. While all three levels of prior experience demonstrate the positive influence of prior experience on firm collaborative benefits, the fact that the increases brought by prior experience do not vary much by the level of experience supports the results reported above. As a final check to see if the existence, rather than extent, of prior experience matters for collaborative benefits, I use a piecewise approach. EXPERIENCE > 0 equals one when a firm has participated in at least one alliance, EXPERIENCE > 5 equals one when a firm has participated in at least six alliances, and EXPERIENCE > 10 equals one when a firm has participated in more than 10 previous alliances. Thus, a firm that has participated in 11 alliances will have all three dummies set to one. With this approach, we can examine the *incremental* benefit of additional experience. Results in Table 2 (column 5) confirm the inferences made above and Hypothesis 1: prior alliance experience matters, but the *extent* of such experience does not seem to affect a firm's ability to benefit from a current alliance.

It is possible that the extent of experience does not seem to effect current outcomes because more extensive experience indicates older experience. That is, extensive experience may indicate a longer history of alliance activity. The value of experience may depreciate over time; that is, older experience may not improve a firm's the ability to manage current alliances. To test whether this is the case, I measure prior alliance experience according to how recent that experience is. That is, I count how many alliances a firm is involved in each of the 6 years prior to the current alliance. For example, EXPERIENCE: 1 YEAR equals the count of alliances in the year immediately prior to the current alliance and EXPERIENCE: 2 YEARS equals the count of alliances in the year that is 2 years prior to the current alliance. Results from this estimation are set out in Table 3.

Results in Table 3(column 1) suggest that the age of prior alliance experience does not affect firm collaborative benefits. All of the parameter

[25] To further demonstrate the significance and importance of the alliance experience variable, I estimated the marginal effects of experience, past patent performance and alliance R&D scope from the parameter estimates set out in Table 2(column 3). These marginal effects show that a firm with prior alliance experience can expect to have 66 more citation-weighted patents than a firm without such prior experience. Similarly, we expect each pre-alliance patent to increase citation-weighted patents *ex post* by 0.22. Thus, it would take approximately 300 pre-alliance patents to have an effect on the dependent variable similar to prior experience (i.e., $300 \times 0.22 = 66$). This demonstrates the strong impact of prior alliance experience relative to pre-alliance firm patenting on the dependent variable. The impact of having either narrow or broad scope (as opposed to intermediate scope) is to reduce the *ex post* citation-weighted patents by over 30 (i.e., a reduction of 31 in the case of narrow scope and 36 for broad scope patents). Since narrow and broad scope cannot take a value greater than 1, the effects of narrow or broad scope alliances cannot exceed the effect of prior experience on collaborative benefits. A similar comparison can be made by examining the marginal effects for parameter estimates from Table 3(column 3). Experience effects dominate the impact of pre-alliance firm patenting and narrow or broad scope on collaborative benefits.

estimates are not significant at any conventional level. I then re-estimate $E[PATENT]$ as a function of the age of prior alliance experience captured via dummy variables, rather than as a count variable. These results appear in Table 3(column 2). This estimation suggests a different story. The existence (rather than extent) of experience in the year immediately prior to the current alliance positively and significantly improves collaborative benefits. Firms with recent alliance experience can expect to improve collaborative benefits by 204 WPC (an increase of 250%) over firms without experience or with less recent experience. Interestingly, only experience in the year immediately prior to the current alliance affects performance. Experience in earlier years has no significant effect. This suggests that knowledge or learning from experience deteriorates rapidly over time and is consistent with earlier findings linking experience and performance (e.g., Argote *et al*., 1990; Baum and Ingram, 1998).

As a robustness check on this result, I aggregate the experience timing dummies into two: experience between 1 and 3 years prior to the current alliance and experience 4 or more years prior to the current alliance. Results from this estimation are set out in Table 3(column 3). These results similarly suggest that experience deteriorates over time. Recent experience (1–3 years prior) improves collaborative benefits by 70 WPC over no prior experience (an improvement of 137%). Recent experience similarly improves collaborative benefits over older experience by 92 WPC, an increase of 317 percent. Interestingly, older experience (4 or more years prior to the current alliance) has a negative effect on current collaborative outcomes. One possible interpretation is that alliance management skills have changed rapidly over the years leading up to the sample timeframe, such that older skills are no longer useful. Firms with this older experience, however, may believe that they have the requisite skills for successful alliance management and may not take the appropriate steps to adopt their skills to the current alliance. That is, firms may be overconfident in their ability to manage current alliances when they have older experience. Firms that continue to exploit existing routines may experience reduced performance if the criteria for success changes after routines are adopted (Baum and Ingram, 1998).

While these results seem robust to various specifications, an alternative explanation for the positive effect of prior experience on collaborative benefits exists. If prior experience is in fact experience with the same partner in the alliance, we may not be able to conclude that firms learn to manage alliances generally with greater experience. The positive effect of experience on performance may be capturing the greater partner specific knowledge, reputation effects, or the development of trust between partners. For example, the existence of prior relationship may indicate a long-term relationship between partners. Assuming that this relationship has some value to all partners, firms can more confidently share technology with their partners since it is less likely that partners will behave opportunistically. Thus, 'calculativeness' (Williamson, 1993), reputation effects (Kreps, 1990), or 'trust' (Gulati, 1995) also suggest a positive link between past alliances and current collaborative outcomes.

To see whether the positive relationship between prior experience and collaborative benefits is due to partner specific relationships, rather than learning from prior alliances, I estimate $E[PATENT]$ as a function of prior experience split into two variables: partner-specific experience and non-partner-specific experience. The results of this estimation are set out in Table 3 (column 4). Here, I estimate the effects of specific and non-specific prior experience on collaborative benefits via dummy variables. From this estimation, we see that prior experience with a specific partner improves collaborative outcomes; the estimate of prior links is positive and significant. Thus, the greater the prior experience with a specific partner, the better are collaborative outcomes in alliances with the same partner. However, this effect does not remove the effect of prior experience generally. Non-specific prior alliance experience still has a positive and significant effect on alliance outcomes. This result is robust to different constructions of variables capturing specific and non-specific experience, including logged counts and various dummy variable configurations.[26] Thus, we can conclude that the effect of prior experience on collaborative benefits

[26] In the interests of brevity, these results are not reported here. Results are available from the author on request.

Table 3. Experience timing, partner-specific experience, and performance

	Count variables (1)	Dummy variables (2)	Aggregated dummies (3)	Partner-specific (4)
INTERCEPT	0.751	−0.229	0.574	0.663
	1.116	1.167	1.199	1.253
EXPERIENCE: 1 YEAR	0.053	1.270***		
	0.043	0.564		
EXPERIENCE: 2 YEARS	−0.001	0.154		
	0.038	0.642		
EXPERIENCE: 3 YEARS	0.007	0.350		
	0.044	0.525		
EXPERIENCE: 4 YEARS	0.011	−0.850		
	0.138	0.682		
EXPERIENCE: 5 YEARS	0.096	−0.597		
	0.251	0.467		
EXPERIENCE: 6 YEARS	−0.040	−0.151		
	0.219	0.713		
EXPERIENCE: 1–3 YEARS			0.862***	
			0.305	
EXPERIENCE: ≥4 YEARS			−0.551*	
			0.399	
PRIOR LINKS > 0 (dummy)				0.447*
				0.284
EXPERIENCE > 0 (dummy)				0.573***
				0.243
FIRM PATENT	0.002***	0.002***	0.002***	0.002***
	0.000	0.000	0.000	0.000
PARTNER PATENT	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000
TECHNOLOGICAL DIVERSITY	13.901***	15.414***	14.057***	14.064***
	3.355	3.497	3.576	3.746
TECHNOLOGICAL DIVERSITY^2	−11.106***	−12.194***	−11.304***	−11.279***
	2.382	2.501	2.511	2.617
SCOPE(Narrow)	−0.229*	−0.344***	−0.282**	−0.291***
	0.145	0.141	0.156	0.141
SCOPE(Broad)	−0.325**	−0.511***	−0.349***	−0.468***
	0.185	0.177	0.173	0.179
MULTILATERAL	0.113	0.111	0.120	0.112
	0.190	0.177	0.189	0.180
INTERNATIONAL	0.004	−0.039	−0.081	−0.002
	0.194	0.191	0.185	0.190
OTHER ALLIANCE	1.046***	1.110***	0.877***	0.781***
	0.246	0.225	0.254	0.252
YEAR(1992)	−0.325	0.316	−0.195	−0.339**
	0.254	0.334	0.201	0.195
YEAR(1993)	−1.167***	−0.453	−0.883***	−1.102***
	0.271	0.358	0.243	0.227
n	1005	1005	1005	1005
Wald chi-square	281.7***	302.2***	211.3***	226.6***
d.f.	17	17	13	13

Negative binomial estimation.
Dependent variable is citation-weighted patents issued to each firm in a post-alliance period.
Positive coefficients indicate increased patent output.
Significant at * 10%, ** 5%, and *** 1% level for one-tailed tests.
Standard errors below coefficients.

is not solely attributable to long-term partner relationships. We cannot disconfirm the above conclusion that firms learn to manage alliances with prior experience.

To test my second hypothesis, that is, that experience matters more for alliances characterized by greater uncertainty, I split the sample into two groups based on alliance characteristics: low uncertainty and high uncertainty. As described in detail in the Appendix, I use the expected probability that firms choose an equity joint venture for their alliance activity to split observations into these two categories. This split allows us to observe the effect of prior experience on outcomes conditional on the degree of uncertainty presented by the alliance characteristics. Results from the estimation are set out in Table 4.

The first two columns in Table 4 report results of prior experience on collaborative benefits using a count of prior alliances. Prior experience for both low- and high-uncertainty alliances positively and significantly affects collaborative outcomes. This result holds across alternative measures of prior experience: a logged count and a dummy variable capturing whether a firm has any prior alliance experience. However, the effects of prior

Table 4. Prior experience, uncertainty, and performance

	Low uncertainty (1a)	High uncertainty (1b)	Low uncertainty (2a)	High uncertainty (2b)	Low uncertainty (3a)	High uncertainty (3b)
INTERCEPT	0.878	−17.669**	0.911	−18.245**	0.981	−18.201**
	1.081	10.713	1.086	10.952	1.142	10.571
EXPERIENCE: COUNT	0.013*	0.042**				
	0.010	0.023				
LOG(EXPERIENCE)			0.181**	0.391***		
			0.104	0.162		
EXPERIENCE > 1					0.607***	0.886***
					0.263	0.365
FIRM PATENT	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	0.000	0.000	0.000	0.000	0.000	0.000
PARTNER PATENT	0.000	0.000*	0.000	0.000*	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000
TECHNOLOGICAL DIVERSITY	12.707***	59.864***	12.711***	61.394***	12.394***	60.416***
	3.351	25.899	3.371	26.455	3.560	25.655
TECHNOLOGICAL DIVERSITY^2	−10.110***	−37.886***	−10.157***	−38.821***	−9.962***	−38.015***
	2.423	15.291	2.434	15.624	2.544	15.193
SCOPE(Narrow)	−0.150	−0.288	−0.170	−0.357	−0.259*	−0.372
	0.197	0.328	0.198	0.334	0.186	0.324
SCOPE(Broad)	0.075	−1.010***	0.061	−1.088***	−0.054	−1.159***
	0.346	0.386	0.337	0.389	0.321	0.380
MULTILATERAL	0.335	−0.147	0.279	−0.186	0.249	−0.089
	0.263	0.373	0.260	0.367	0.254	0.353
INTERNATIONAL	0.096	−0.486	0.062	−0.512	0.083	−0.587
	0.212	0.469	0.207	0.470	0.213	0.463
OTHER ALLIANCE	1.175***	0.834***	1.041***	0.523	0.889***	0.531
	0.277	0.397	0.284	0.429	0.292	0.427
YEAR(1992)	−0.368**	−0.492*	−0.384**	−0.407	−0.394**	−0.363
	0.219	0.383	0.224	0.363	0.224	0.330
YEAR(1993)	−1.361***	−0.731**	−1.393***	−0.707**	−1.413***	−0.592*
	0.286	0.431	0.292	0.422	0.282	0.380
n	669	336	669	336	669	336
Wald chi-square	175.9***	111.1***	166.4***	106.1***	180.5***	102.0
d.f.	12	12	12	12	12	12

Negative binomial estimation.
Dependent variable is citation-weighted patents issued to each firm in a post-alliance period.
Positive coefficients indicate increased patent output.
Significant at * 10%, ** 5%, and *** 1% level for one-tailed tests.
Standard errors below coefficients.

experience are far more pronounced for alliances characterized by greater uncertainty. For all three measures, the coefficient on prior experience for high-uncertainty alliances is statistically significant and nearly double the coefficient estimate for low-uncertainty alliances.[27] Using results from Table 4(3), experience appears to improve collaborative benefits from low-uncertainty alliances by 45 WPC, while such experience improves benefits from high-uncertainty alliances by 62 WPC—a difference of 17 WPC (or an increase of 38%). These results suggest that prior experience matters more for collaborative benefits from alliances with high uncertainty. Outcomes from complex or uncertain activities rely more on judgment and, consequently, prior learning experiences, than do simpler, more predictable tasks. As such, firms with greater experience that collaborate in R&D on projects that are, for example, long term in nature with highly uncertain outcomes are better able to manage these alliances to realize benefits from collaboration. Support for Hypothesis 2 is found.[28]

Estimates of the effects of control variables across specifications are largely as expected and consistently with prior research. A firm's prior patenting activity significantly increases post-alliance patenting. Several interpretations of this significant relationship are possible. First, strong prior alliance patenting may indicate a firm's propensity to patent such that firms that patent much in the past are more likely to patent in the future. Similarly, prior (unweighted) patenting also proxies for the level of R&D inputs, such as R&D spending or technological acquisitions; results across Tables 2 to 4 suggest that R&D outputs rise with inputs. Given that prior patenting is such a broad control variable, other possible interpretations of this result are that larger firms patent more, firms that may be diversified across industries have a broader patent pool and firms that are more effective at R&D patent more. Interestingly, though, partner patenting does not seem to affect firm patenting in most specifications. This suggests, perhaps not surprisingly, that a firm's own pre-alliance patenting activity is a much better predictor of post-alliance patenting than partner patenting activity is. Technological diversity between partners initially increases the collaborative benefits post alliance, but this relationship turns negative at an intermediate level of technological diversity. This result is consistent with prior research (e.g., Sampson, 2000). Narrow alliance scope reduces post-alliance benefits from collaboration, as expected. Firms engaging in narrow R&D activities reap reduced collaborative benefits when compared to firms allying in intermediate breadth R&D. This suggests, not surprisingly, that more limited alliance R&D activities yield more limited results. While the sign of this result holds across all specifications, coefficient estimates are not consistently significant across specifications. Counter to expectations, broad scope seems to reduce post-alliance collaborative benefits. One possible explanation for this somewhat counter-intuitive result is that payoffs from such broad alliances are not adequately captured in a 4-year, post alliance window. Alternatively, it is possible that a broad alliance signals a poorly defined alliance goal, which may dampen performance. Firm collaborative benefits do not appear to be affected if the alliance involves more than two partner firms nor if the alliance is international; neither MULTILATERAL nor INTERNATIONAL is statistically significant across specifications. In contrast, the existence of other concurrent alliances does positively affect firm patenting post alliance, as expected. Finally, the commencement year dummies, signaling that the alliance commenced in either 1992 or 1993 rather than 1991, are both negative and significant, reflecting the inevitable truncation of citations on patents applied for later in the sample. Overall, these results show positive effects from alliance experience, suggesting that firms may learn to manage with experience in the context of R&D alliances.

[27] As noted in the Appendix, the sample of alliances may be split at several different threshold levels to test the effect of experience on collaborative benefits conditional on alliance characteristics. While I only report results here from one such threshold (i.e., Prob[EJV] = 0.20), results are not sensitive to the choice of threshold. At all thresholds tested, the effect of prior experience is always positive and significant for both low- and high-uncertainty alliances and this effect is always larger for high-uncertainty alliances. These results are available on request.

[28] Alliance uncertainty may also be captured via the actual selection of an equity joint venture for alliance organization, rather than the probability that an equity joint venture is selected. For robustness, I replicate Table 4 using the selection of an equity joint venture as a signal of the underlying alliance uncertainty. Results are substantively the same, with the same sign and statistical significance, as those reported in Table 4. These results are available on request.

DISCUSSION AND CONCLUSION

From the learning curve literature, we know that firms can reduce the costs of production with each additional unit of output. In this sense, firms improve production by 'doing.' Do firms, however, learn to manage with additional management experience? While the popular press seems to indicate, at least in the context of alliances, that firms can learn to manage by doing, we have only limited empirical evidence to support this claim. This paper provides further evidence that firms may learn how to manage alliances with experience, with a sample of 464 R&D alliances in the telecommunications equipment industry. While collaborative benefits are enhanced with prior alliance experience, more extensive experience does not appear to improve outcomes over more limited experience. The lack of impact of additional experience on outcomes may well be attributable to the age of such experience; the benefits of prior alliance experience depreciate rapidly over time.

There are several possible explanations for the apparent depreciation of experience over time. Optimal alliance management techniques may be changing rapidly over time, such that only the most recent experience offers lessons for current alliance management. This may be particularly so in industries experiencing rapid technological change, such as the telecommunications equipment industry. Thus, firms may be experiencing a competency trap. After learning from initial experience, firms develop and exploit best practices, which may supplant further exploration and prevent the firm from adopting new, more productive practices. Alternatively, managerial turnover may explain the lack of cumulative benefits from prior experience. Alliance management skills may be embedded in specific managers, such that turnover adversely affects the ability of a firm to reap long-term benefits from prior collaborative experience. This suggests that firms may learn from their prior experience managing alliances but that the skills gained from such experience are only productive for a short period of time.

Whether this depreciation is due to inertia, 'lock-in' to currently productive routines, or turnover and the resultant lack of organizational memory, this result has important implications for firms using alliances as a key part of their strategy. Alliance management offices, as argued by Kale, Dyer, and Singh (2001), may play a critical role in ensuring continued learning, assimilation, and diffusion of best practices within an organization. Firms need some means of preventing inertia and reliance on exploitation at the expense of exploration. Further, firms need a means for institutionalizing best practices gained from each alliance to protect against loss with managerial turnover.

Recording and codification of learned practices through dedicated alliance management offices may provide a means of organizational memory to prevent loss through personnel turnover. However, having a repository of alliance management techniques or identified alliance success factors may not be enough to ensure the benefits of prior alliance experience. Some coordination is probably required to ensure retention and transfer of learned practices and routines across a firm's alliances. As Nelson and Winter (1982: 104) note, 'an organization does not become capable of an actual productive performance merely by acquiring all the "ingredients," even if it also has the "recipe." What is central to a productive organizational performance is *coordination*' (emphasis added). Thus, the coordinating function, such as by a director of alliance management, who oversees the allocation of personnel to alliances as well as recording and retrieval of best practices, is likely a critical component of alliance management success. One such director of alliance management interviewed summed up the important tasks of an alliance management coordinator as follows:

> When we actually implement the alliance, we make sure that one of the alliance managers in our organization is there to make sure that the behavioral principles, the communication planning, the cultural understanding and many other aspects are set firmly before the project is actually initiated ... Once an alliance is up and running, we're there to help preempt issues that can arise, particularly from a relationship perspective, and make sure that both parties are doing the right thing in terms of communication, sharing knowledge, and managing towards a commonly agreed strategic goal and making sure that there is no deviation from that path ... We're involved in every alliance.

Dedicated alliance management resources may be even more important for firms that engage in complex alliances. Results here suggest that prior learning experiences are more important for alliances characterized by greater uncertainty.

Firms rely more on informal knowledge when faced with highly uncertain situations, such as more complex alliances, than firms facing simpler, more stable situations (Klein, 1998; Levitt and March, 1988; Ouchi, 1980). A system for retention and diffusion of alliance management practices along with an ability to update practices over time is more critical to alliance performance when firms cannot easily evaluate the contributions of their partners, the likely trajectory of the joint R&D program, and the transfer of knowledge across organizational boundaries.

On a broader level, this research is suggestive of the importance of 'dynamic capabilities' (e.g., Teece, Pisano, and Shuen, 1997). Teece *et al.* (1997) argue that firms achieve and sustain competitive advantage by renewing competences in response to environmental shifts. Indeed, a positive link between *recent* experience and performance may reflect the importance of dynamic capabilities; what matters to a firm's ability to benefit from collaboration is not a long history of alliance experience, but recent experience, signaling the importance of adaptations to the current competitive environment. As argued by Eisenhardt and Martin (2000), dynamic capabilities are most important in industries experiencing rapid technological change, such as the industry studied here, since these capabilities allow firms to adapt to new environmental conditions. In the context of alliances, dynamic capabilities may take the form of the specialized alliance management offices discussed above, involving 'specialized personnel who are committed full time to their change roles' (Winter, 2003: 993). As a link between past experience and challenges in current alliances, such offices may facilitate more successful alliances by assimilating and diffusing lessons learned from recent experience. A useful extension to this work would be to examine whether these experience effects are as important and depreciate as quickly in technologically stable industries.

The discussion above suggests that further work is necessary to link experience, differences in alliance management practices between firms and performance. For example, does experience benefit all firms equally, or more so in those with dedicated alliance management resources? Further, we might expect there to be important differences between alliance management effectiveness, as argued by Kale *et al.* (2001), with some alliance management offices better at retention, some better at the learning process, and others best at the coordinating role. Finally, we might expect that the alliance management offices are more important for firms involved in complex alliances. Greater exploration of differences in dedicated alliance resources across firms and whether these differences affect the relationship between experience and performance will help shed light on these questions.

While this work has many interesting implications, important limitations exist. First, while we can capture the number of prior alliances a firm has been involved in, we cannot judge the size or breadth of each alliance. We might expect that more substantial prior alliances contribute more to a firm's experience bank and may, therefore, improve current collaborative benefits to a greater extent than smaller or less substantial prior alliances. Of course, collecting more detailed data on the breadth of prior alliances presents its own limitations—such data are likely only available via survey and would reduce the scale of the study substantially. While such a study would be a valuable one, the nature of the data will make it more difficult to make large-scale inferences about the links between experience and firm collaborative benefits. Second, no hypotheses are made here about whether the same experience will affect allying firms differently. For example, when two firms ally, one firm may benefit more from the experience than the other, perhaps due to the existence or greater competence of that firm's alliance management resources. Further work is required to identify those firms with prior experience who do and do not have alliance experience to see if such dedicated resources do offer a means for developing organizational memory and the important coordination function described by Nelson and Winter (1982). Finally, further studies of the effects of experience on collaborative benefits in alliances not involving R&D (such as pure manufacturing or marketing alliances) would be a useful extension to this work. There are reasons to believe that experience matters more in R&D alliances, such as suggested by Anand and Khanna (2000a), and the results presented here may or may not extend to other types of alliances.

Despite these limitations, this study provides important evidence of the effects of experience on performance and how these effects differ based on the age of the experience and complexity presented by the current alliance. These results have clear implications for alliance management and the importance of the increasingly common alliance management offices within firms. While we must take care generalizing the findings here, the evidence presented here is another step towards understanding the importance of adaptation, here captured via learning from experience, on organizational performance.

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APPENDIX: CALCULATING ALLIANCE UNCERTAINTY

To assess the complexity and uncertainty of alliance activities, I use the expected probability that firms select an equity joint venture over a more contractual form of alliance organization ('bilateral contract'). The bilateral contract is an agreement to collaborate in R&D, where partners combine or pool their capabilities but do not form a separate legal entity for their collaborative efforts. Partners may similarly pool their capabilities in an equity joint venture, but also form a separate legal entity for their collaboration. Several empirical studies in the transaction cost economics literature have tested the relationship between alliance characteristics and the choice between these organizational forms (e.g., Oxley, 1997, 1999; Pisano, 1989; Sampson, 2004a, 2004b). According to this literature, firms choose an equity joint venture for their collaborations when specifying partner rights and obligations is difficult and monitoring and enforcement are imperfect. These conditions generally hold when alliance activities are complex, such as ambitious 'next-generation' R&D projects with long-term time frames and highly uncertain outcomes, and when external property rights are weak (Oxley, 1999; Sampson, 2004b). An equity joint venture is typically selected in these cases because it relieves partner firms from full, contractual specification and provides means and incentives for firms to respond to unanticipated contingencies. However, given the cost of set up and bureaucratic costs associated with the equity joint venture, firms only choose an equity joint venture when alliance activities are reasonably uncertain or complex and difficult to coordinate as a result. Thus, the characteristics that drive selection of an equity joint venture are the same characteristics we expect to reveal the degree of uncertainty or complexity attending alliance activities. As such, the probability that an equity joint venture is selected is a useful indicator of the uncertainty surrounding alliance activities.

The advantage of using this probability estimate is that it allows comparison between alliances across multiple dimensions. According to Rosenbaum and Rubin's (1983) propensity score theorem, alliances with the same probability estimate have the same distribution over the full vector of variables capturing alliance characteristics. By dividing the sample according to this estimate, we can have confidence in the comparability of alliances within each subsample. To calculate this score, I use a probit model to estimate the probability that allying firms select an equity joint venture for their alliance organizational form. Following Sampson (2004b), I estimate this probability as a function of the following variables:

1. Whether there are more than two partner firms in an alliance.
2. Whether alliance activities include marketing, manufacturing or supply in addition to joint R&D.
3. The breadth of alliance R&D activities (narrow, intermediate or broad).
4. The overlap of partner firm technological portfolios.
5. Whether partners have allied previously.
6. The extent of prior alliance experience the allying firms have generally.
7. The institutional environment of the partner firm home nations, including strength of intellectual property and contract law regimes, political risk and cultural differences between partners.

The results of this estimation are consistent with prior studies of alliance organizational form choice (Oxley, 1997, 1999; Pisano, 1989).

I then split the observations into two subsamples: low- and high-uncertainty alliances. I begin with a threshold of Prob[Organization = EJV] = 0.20. That is, all alliances with a probability estimate equal to or less than 0.20 are categorized as low uncertainty, while alliances with a score of greater than 0.20 are categorized as high uncertainty. While the usual threshold for predicting organizational form = 1 (i.e., equity joint venture) is 0.50, I adjust the threshold downward to reflect the unbalanced nature of the sample: bilateral contracts far outnumber equity joint ventures. As Greene notes:

> If the sample is relatively unbalanced, that is, has many more 1s than zeros, or vice versa, then by [the 0.50] prediction rule, [the model] might never predict a 1 (or zero). To consider an example, suppose that in a sample of 10,000 observations, only 1000 have Y = 1. We know that the average predicted probability in the sample will be 0.10. As such, it may require an extreme configuration of regressors even to produce an [probability] of 0.20, to say nothing of 0.50. . . . The obvious adjustment is to reduce [the threshold]. (Greene, 1990: 652)

Here the ratio of bilateral contracts to equity joint ventures is over five to one. Thus, we expect to observe a probability of 0.50 or greater in fewer than 20 percent of cases, if at all, since the maximum likelihood procedure is not designed to minimize incorrect predictions (Amemiya, 1981; Greene, 1990). Results reported in Table 4 use the 0.20 threshold. These results are substantially the same as those produced using 0.30 and 0.40 thresholds: signs, significance levels and relative coefficient magnitudes between subsamples are all the same.