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TECHNOLOGICAL ACQUISITIONS AND THE INNOVATION PERFORMANCE OF ACQUIRING FIRMS: A LONGITUDINAL STUDY

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This paper examines the impact of acquisitions on the subsequent innovation performance of acquiring firms in the chemicals industry. We distinguish between technological acquisitions, acquisitions in which technology is a component of the acquired firm's assets, and nontechnological acquisitions: acquisitions that do not involve a technological component. We develop a framework relating acquisitions to firm innovation performance and develop a set of measures for quantifying the technological inputs a firm obtains through acquisitions. We find that within technological acquisitions absolute size of the acquired knowledge base enhances innovation performance, while relative size of the acquired knowledge base reduces innovation output. The relatedness of acquired and acquiring knowledge bases has a nonlinear impact on innovation output. Nontechnological acquisitions do not have a significant effect on subsequent innovation output.

In this paper we examine the impact of acquisitions on the subsequent innovation performance of acquiring firms. Studying the impact of acquisitions on postacquisition innovation performance is important from at least three perspectives. First, this evaluation is important from the perspective of organizational learning and innovation, and helps us understand how organizations absorb and use external knowledge. Firm-level theories of technical change suggest that a firm's innovativeness is an outcome of increases in its knowledge base (Griliches, 1984, 1990; Pakes and Griliches, 1984; Henderson and Cockburn, 1996). While a firm's knowledge base can grow through a series of knowledge-enhancing investments by the company over time, firms can also grow their knowledge through acquiring or 'grafting' of external knowledge bases (Cohen and Levinthal, 1989; Huber, 1991). Interestingly, while the relationship between firms' investments in knowledge and their innovation output has been studied extensively (Hall, Griliches and Hausman, 1986; Griliches, 1990), relatively little research has focused on the role of acquisitions in growing the firm's knowledge base (Granstrand and Sjolander, 1990; Huber, 1991; Gerpott, 1995). This lacuna is all the more surprising given findings which indicate that obtaining technological know-how and developing technical capabilities are increasingly important motives for acquisitions (Link, 1988; Granstrand *et al.*, 1992; Chakrabarti, Hauschildt, and Suverkrup, 1994; Wysocki, 1997a, 1997b).

Scholars studying the market for corporate control have also examined the relationship between acquisitions and innovation output (Hitt *et al.*, 1991, 1996; Hoskisson, Hitt, and Ireland, 1994). However, in contrast to the findings of the innovation literature, studies in the corporate control tradition have generally found that acquisitions have a negative impact on the postacquisition innovation output of acquiring firms. Agency problems, reduction in managerial commitment to

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innovation, and the absorption of managerial energy in the acquisition integration process at the expense of routine management have been posited as possible explanations for these results (Hitt *et al.*, 1991, 1996). This conclusion, however, is puzzling since acquisitions continue to be a popular strategy for corporate growth. In recent years more dollars have been invested in acquisition activity than in any other equivalent time period in history (Curry, 1997). Evaluating the postacquisition innovation output of acquiring firms provides one indicator, albeit an indirect one, of the returns to corporate investments in acquisition activity.

A third reason for studying the impact of acquisitions on the postacquisition performance of acquiring firms comes from the growing literature on the resource-based view of the firm. According to this perspective acquisitions are an important part of the business process of redeploying resources into more productive uses (Anand and Singh, 1997; Capron, Dussauge, and Mitchell, 1998; Capron, Mitchell, and Swaminathan, 1998). Through acquisitions firm-specific assets housed within one organization are merged with assets in another organization to improve the productivity of the combined assets (Haspeslagh and Jemison, 1991; Anand and Singh, 1997). Evaluating the postacquisition performance of firms provides evidence on the efficiency of this asset-matching and combining process.

In this paper we draw upon theories of technological innovation, learning, and the resource-based view to develop a theoretical model and predictions relating acquisition characteristics to the innovation performance of acquiring firms (Cohen and Levinthal, 1989; Grant, 1996). Innovation performance can be measured in terms of innovative inputs such as R&D expenditures, or innovation outputs such as patenting frequency (Griliches, 1984; Henderson and Cockburn, 1996). Acquisitions can affect both innovative inputs and innovative outputs (Hitt *et al.*, 1991). For instance, a firm's R&D expenditures can decrease after it conducts an acquisition as the firm eliminates certain streams of research or as managers become more risk averse (Hitt *et al.*, 1991). Yet, even while research efforts decrease, the productivity of those efforts can increase as the two hitherto separate research teams combine their skills and knowledge. In this research we focus on the impact of acquisitions on innovation *outputs* as measured by the patenting frequency of the acquiring firm. Accordingly, we adopt an innovation production function framework and model patenting frequency as the output of a production function (Griliches, 1984). The hypotheses of this study are statements about the relationship between this patented knowledge output and the firm's stocks of owned and acquired knowledge. In estimating the impact of acquisitions on the innovative output of a firm we statistically control for the levels of innovative inputs such as R&D expenditures, but leave their substantive examination to future work.

HYPOTHESES

In this research we focus on two contingencies that may be critical to clarifying the relationship between acquisitions and the postacquisition innovation performance of acquiring firms. First, we draw attention to the fact that technological reasons do not motivate all acquisitions. For example, acquisitions can be motivated by the desire to obtain access to distribution channels, to gain entry into new markets, or to obtain financial synergies or market power (Lubatkin, 1983; Balakrishnan, 1988; Chatterjee, 1991; Haspeslagh and Jemison, 1991; Capron, Dussauge, and Mitchell, 1998). Such acquisitions may provide no technological inputs to the acquiring firm and therefore cannot be expected to improve its innovation output. Second, we note that even among technologically motivated acquisitions the impact of acquisitions may depend on the characteristics of the relationship between the knowledge of the acquired and acquiring firms (Lubatkin, 1983; Singh and Montgomery, 1987; Lane and Lubatkin, 1998).

In summary, we argue that the impact of acquisitions on the acquiring firm's innovation output can be understood in the context of the technological inputs provided by the acquisition. We argue that acquisitions that provide no technological inputs cannot be expected to have a positive impact on firm innovation output (Hypothesis 1). Second, within acquisitions that do provide technological inputs, we predict that the impact of an acquisition on the postacquisition innovation output of the acquiring firms is likely to vary positively with the absolute size of the acquired firm's knowledge base, negatively with the relative size of the acquired and acquiring knowledge bases, and curvilinearly with the relatedness of the acquired and acquiring knowledge bases (Hypotheses 2, 3 and 4).

Technological vs. nontechnological acquisitions

Acquisitions can affect the acquirer's subsequent innovation output through two possible mechanisms. First, an acquisition of another firm can be viewed as an absorption of the acquired firm's knowledge base into the acquiring firm's knowledge base. Such a union can potentially expand the acquirer's knowledge base and increase its innovation output by providing economies of scale and scope in research and by enhancing the acquirer's potential for inventive recombination (Henderson and Cockburn, 1996; Fleming, 1999). Since nontechnological acquisitions add less to the knowledge base of the acquirer they are less likely to lead to such innovation output-enhancing effects.[1] However, an acquisition can also disrupt the established routines of the acquiring firm and those of its newly acquired component, and thereby reduce productivity (Jemison and Sitkin, 1986; Haspeslagh and Jemison, 1991). Prior research suggests that acquisition integration entails far-reaching disruption, and involves significant managerial attention and transactions costs (Pritchett, 1985; Haspeslagh and Jemison, 1991; Hitt *et al.*, 1991, 1996; Hoskisson *et al.*, 1994). However, whether this disruption related to nontechnological acquisitions will produce a negative impact on innovative productivity is not clear, *a priori*. On one hand it is possible that as management focuses more on acquisitions and their integration, decision making on routine technological matters can be delayed, activities such as product championing can suffer, and a crisis mentality on the management of the acquisition can lead to only residual energies being supplied to day-to-day operations even in the technological core of the company (Thompson, 1967; Pritchett, 1985; Hitt *et al.*, 1996). Alternately, it is possible that since such acquisitions do not involve a technological component by definition, they may not affect the technological subsystem (Thompson, 1967) and innovation routines of the firm, and therefore have no impact on innovation output at all. The final impact of an acquisition depends on the degree to which these effects come into play.

Accordingly, we present the following base hypothesis:

Hypothesis 1: Nontechnological acquisitions will affect the postacquisition innovation output of acquiring firms either negatively or nonsignificantly.

Technological acquisitions and the absolute size, relative size, and relatedness of knowledge bases

Technological acquisitions are acquisitions that provide technological inputs to the acquiring firm. Thus, they potentially expand the acquirer's knowledge base and provide scale, scope, and recombination benefits (Henderson and Cockburn, 1996; Fleming, 1999). However, technological acquisitions can also entail a disruption in organizational routines. Further, this disruption is most likely in the set of routines that are closest to the innovation arena, the technological subsystem of the firm. Thus, technological acquisitions can also have a negative impact on the innovation output of the acquiring firm. On balance, assessing whether technological acquisitions will have a positive or negative impact on postacquisition innovation output is likely to depend upon the quantity and nature of knowledge elements that they bring to the acquiring firm. To evaluate whether the scale, scope, and inventive recombination benefits of acquisitions outweigh their negative effects on organizational routines we compare the knowledge bases of acquired and acquiring firms along three key characteristics that have also been prominently used in prior acquisition research: absolute size, relative size, and relatedness (Lubatkin, 1983). In the following sections we examine and develop distinct hypotheses for each of these characteristics.

Absolute size of acquired knowledge base

The absolute size of an acquired knowledge base can affect the post acquisition innovation output of the acquiring firm through at least two mechanisms, both indicating a positive effect of larger

[1] As suggested by one of the reviewers, in some cases nontechnological acquisitions can increase innovation output, for instance by providing contacts with new customers.

knowledge bases. First, the integration of the two hitherto separate knowledge bases may enable enhanced economies of scale and scope (Henderson and Cockburn, 1996). For instance, a long tradition of research in technology suggests that new innovative outputs are often the result of recombining existing elements of knowledge into new syntheses (Schumpeter, 1934; Henderson and Clark, 1990; Kogut and Zander, 1992; Tushman and Rosenkopf, 1992; Utterback, 1994; Fleming, 1999). From this combinatorial perspective, the number of direct combinations that a firm can create from its own knowledge elements increases with the size of the acquired knowledge base. While a firm with five units of knowledge can generate 10 combinations using two elements at a time, acquiring another firm with three units of knowledge increases the number of combinations that become available to 28. Similarly, the merger of two knowledge bases can also provide scale or scope economies by reducing duplication in research efforts or by providing a larger research base to defray costs.

Second, acquiring a larger knowledge base may enhance a firm's absorptive capacity. Prior research indicates that as a firm expands its internal knowledge base and technological capability, it also enhances its ability to absorb and utilize external knowledge (Cohen and Levinthal, 1989; Cohen and Levinthal, 1990). Thus, when a firm acquires a knowledge base it obtains access not only to the acquired firm's internally created knowledge but also to a larger external domain of knowledge that is understood and used by the acquired firm. Thus, acquisitions increase the number of elements of both internal and external knowledge that are available to the acquiring firm and hence increase its potential for inventive recombination. Hence, we hypothesize:

> *Hypothesis 2: The greater the absolute size of the acquired knowledge base, the greater the subsequent innovation output of the acquiring firm.*

Relative size of acquired knowledge base

The arguments above focused on the increased scale, scope, and recombination benefits possible through the acquisition of a knowledge base. Yet, several steps must be completed before newly acquired knowledge can improve the acquirer's performance. The acquirer needs to recognize the value and content of the acquired knowledge, assimilate it, and apply it (Cohen and Levinthal, 1990). The degree to which these tasks can be successfully accomplished is likely to vary with the relative size of the acquiring and acquired knowledge bases. The larger the *relative* size of the knowledge base to be integrated, the more difficult these stages are likely to be, and the more negative the impact on postacquisition innovation output.

Knowledge is primarily transferred through interactions between the acquired and acquiring units, and entails both teaching and learning on both sides (Haspeslagh and Jemison, 1991). Integration teams, meetings within and between the two R&D units, and extensive face-to-face communication are integral parts of the process by which the merging units learn about each other's technology and processes (Gerpott, 1995). Since every communication needs both a sender and a receiver, the relative size of the knowledge bases in the merger becomes relevant. If the merged knowledge bases are relatively equal in size, most of the knowledge resources of the combined firm will be devoted to the task of integrating the two knowledge bases. As the two approximately equal groups educate each other, fewer resources will be available for conducting the actual business of innovation. On the other hand, if the two knowledge bases are relatively dissimilar in size, the absorption and assimilation activity will occupy only a part of the larger group's resources even if it entails the preoccupation of the smaller of the two groups.

A second dimension of the relative size effect is the disruption of existing organizational routines (Haspeslagh and Jemison, 1991; Singh and Zollo, 1997). For successful assimilation and application of the newly acquired knowledge, many changes have to be introduced into the functioning of the organization. Pathways of communication, routing of work and authority, and formal and informal organizational structures all have to be adapted to incorporate the acquired unit's knowledge (Gerpott, 1995). If the acquired firm's knowledge base is small relative to the acquirer the modifications required are likely to be minor, and therefore not be very disruptive. However, if the acquired firm's knowledge base is large relative to the acquiring firm, fairly major changes would have to be made in the acquiring firm, leading to a significant disruption of existing processes. Accordingly, we predict:

Hypothesis 3: The greater the relative size of the acquired knowledge base, the less the subsequent innovation output of the acquiring firm.

Relatedness of acquired and acquiring knowledge bases

The third critical dimension in the unification of two knowledge bases is their relatedness (Lubatkin, 1983; Singh and Montgomery, 1987; Lane and Lubatkin, 1998). While the previous arguments concerned the *magnitude* of the acquired and acquiring knowledge bases the relatedness argument concerns the *content* of these knowledge bases. We predict that relatedness between the acquired and acquiring knowledge bases is likely to have a nonmonotonic influence on the subsequent innovation performance of acquiring firms. Innovation output will increase with increasing relatedness, but beyond some optimum innovation output will decrease with increasing relatedness.

The absorptive capacity argument suggests that the ability to use new information to solve problems is enhanced when the new knowledge is related to what is already known (Cohen and Levinthal, 1990). Elements of similar knowledge facilitate the integration of the acquired and acquiring knowledge bases (Kogut and Zander, 1992; Grant, 1996). Common skills, shared languages, and similar cognitive structures enable technical communication and learning (Cohen and Levinthal, 1989; Lane and Lubatkin, 1998). Further, the recipes for conducting research, or the innovation routines of the acquired and acquiring firms, are also likely to be different if the firms come from distant realms of technology (Kogut and Zander, 1992; Spender, 1989). In such circumstances the integration of knowledge bases can be resource consuming, or even counterproductive as routines inappropriate to either or both knowledge bases can be adopted (Haspeslagh and Jemison, 1991; Singh and Zollo, 1997).

On the other hand, an acquired knowledge base that is too similar to the acquiring knowledge base may also contribute little to subsequent innovation performance. From an absorptive capacity perspective acquired knowledge can help improve performance through two effects. First, acquired knowledge can provide a cross-fertilization effect as old problems can be addressed through new approaches, or by a combination of old and new approaches (Cohen and Levinthal, 1990). Second, new acquired knowledge can serve as the basis for absorbing additional stimuli and information from the external environment. If an acquisition brings in knowledge that is too closely related to the existing knowledge base of the acquiring firm, both these benefits might be limited.

Knowledge bases with moderate degrees of relatedness provide the benefits of enhancing the variety of possible combinations that the firm can use, while maintaining the elements of commonality that facilitate interaction between the acquired and acquiring knowledge bases. Based on the above arguments we suggest that acquisitions that are characterized by a moderate degree of overlap in the knowledge bases are likely to provide the most significant positive impact on the acquiring firm's subsequent innovation output. Accordingly, we predict:

Hypothesis 4: The relatedness of the acquired knowledge base will be curvilinearly (inverted U) related to the subsequent innovation output of the acquiring firm.

DATA AND METHODS

Organizational knowledge base

In the previous section we argued that an acquisition can be viewed as the union of two knowledge bases. Measuring an organizational knowledge base is then the key operational issue in testing the hypotheses. Specifically, we need to identify empirical measures that capture the absolute size, relative size, and relatedness of knowledge bases. In the arguments below we suggest that an organization's patent portfolio provides a means for capturing these dimensions and mapping an organization's knowledge.

A patent, by definition, represents a unique and novel element of knowledge. A set of patents then represents a collection of discrete, distinct units of knowledge. Identifying a set of patents that a firm has demonstrated familiarity with, or mastery of, can be a basis for identifying the 'revealed' knowledge base of a firm, the distinct elements of knowledge with which the firm has revealed a relationship (Kim and Kogut, 1996).

The patents owned by a firm represent the knowledge that the firm is acknowledged as having created (Jaffe, Trajtenberg and Henderson, 1993). Such patents are naturally elements of the firm's knowledge base. However, the firm's patents also build on prior patents, the knowledge created by the same firm in the past or by other firms which have preceded it in that line of inquiry. These prior patents are cited in the patents as recognition of their contribution to the knowledge embodied in the focal patent. By creating a patent that builds on these prior patents, the firm provides evidence that the knowledge contained in those past patents is a part of the firm's knowledge set. Thus, the patents cited by the firm should also be included in its knowledge base. The Appendix describes in more detail the logic underlying this approach to measuring organizational knowledge bases.

Using patent data to measure organizational knowledge bases corresponds closely to the conceptual abstraction of a firm's knowledge base as a set of knowledge elements (Grant, 1996). The number of cited and obtained patents provides a measure of the size of the knowledge base. The individual patents in the firm's knowledge base provide the basis for comparing the firm's knowledge base with other knowledge bases. Since each patent number uniquely identifies a distinct component of knowledge, the higher the number of patents that are common across two knowledge bases, the higher the relatedness between those knowledge bases (see also Stuart and Podolny, 1996; Mowery, Oxley and Silverman, 1998).

Methods

A panel data design was used to test the hypotheses. We selected a sample of firms from the global chemicals industry independent of their acquisition behavior, and traced the acquisition behavior of these firms over a 12-year period, from 1980 to 1991 (more details on the sample are provided later). Several of the sample firms were very active in the acquisitions arena, while others conducted few or no acquisitions at all. We attempted to collect data on every acquisition conducted by these firms. The acquisition characteristics of these firms were modeled as time-varying influences on the subsequent innovation performance of these firms. A distributed lag analysis was used to identify the effects of an acquisition on innovation performance in the 4 years succeeding the acquisition.

This approach addresses several methodological problems that arise in evaluating the impact of acquisitions on the postacquisition performance of acquiring firms. First, examining a single industry over a common period controls for industry and period effects that have been cited as a problem with prior acquisition research (Fowler and Schmidt, 1988). Second, this research design naturally includes both firms that are active in acquisitions and those that are inactive. In the absence of the latter group of firms it is difficult to refute the argument that good or bad performance by acquiring firms was not shared by similar nonacquiring firms (Fowler and Schmidt, 1988). Third, this approach resolves the problem of handling firms with multiple acquisitions. To reduce the problem of confounding caused by firms making several acquisitions over the study period, some researchers have omitted such firms from analyses (Fowler and Schmidt, 1988). However, omitting such firms may lead to biased findings. With our research design such firms can be retained in the analysis by including acquisition and firm characteristics as time-varying covariates in a panel regression. Finally, our panel data set includes distributed lag effects. The distributed lag technique enables us to use multiple-period lagged values of the independent variables as additional regressors in the estimated equation (Judge *et al.*, 1988). By using this approach, we can, in principle, trace the effects of the acquisition on the performance of the acquiring firm for several periods after the acquisition.

Model specification and econometric issues

We now describe our econometric approach, followed by a discussion of the industry setting and the variables used to test the hypotheses. The dependent variable of the study, innovation output, as measured by patent counts, is a count variable and takes only non-negative integer values. The linear regression model's assumptions of homoskedastic, normally distributed errors are thus violated. A Poisson regression approach is appropriate for such data (Hausman, Hall, and Griliches, 1984; Henderson and Cockburn, 1996). Accordingly, we specified the following Poisson regression model:

$$P_{it} = \exp\,(X_{it-1}\gamma + A_{it-1}\beta_1 + A_{it-2}\beta_2 + A_{it-3}\beta_3 + A_{it-4}\beta_4) \qquad (1)$$

where P_{it} is the number of patents obtained by firm i in year t, X_{it-1} is a vector of control variables affecting P_{it}, and $A_{it\text{-year}}$ is the lagged vector of the acquisition variables for years $t-1$ to $t-4$.

Intuitively, this specification implies that the number of patents obtained by any firm in any year is randomly distributed following a Poisson process, where the covariate vectors X_{it-1} and A_{it-1}, A_{it-2}, A_{it-3}, and A_{it-4} determine the mean of this process. Changes in the value of individual covariates thus influence patenting frequency by affecting the mean of the Poisson distribution from which observations are drawn, in a manner identical to an ordinary regression.

Since the impact of an acquisition is likely to be felt over a number of years, rather than entirely in any one year, we used a distributed lag model (Judge *et al.*, 1988). To capture the lag effects, the one-period, two-period, three-period, and four-period lagged values of all acquisition related variables were included as covariates in the above model. This distributed lag model tests the impact of acquisitions for up to 4 years after the year the acquisition was originally made. Thus, illustratively speaking, in these models the acquiring firm's innovation performance in 1986 is potentially influenced by acquisitions made in 1982, 1983, 1984, and 1985. In sensitivity tests (results available from the authors), instead of using four lags we also estimated the models using three and five lags and found results substantively identical to those reported here.

The use of distributed lags provides two benefits. First, it enables us to examine the time pattern of the impact of acquisitions on firm innovation output. For instance, if an acquisition contributes to improved performance for the first 2 years but thereafter leads to no further improvement in innovation output, the 1- and 2-year lagged acquisition variables will be positive and significant, while the 3- and 4-year lagged acquisition variables will be nonsignificant. Second, since the total impact of an acquisition is likely to be distributed over several periods following the acquisition and may be statistically inconsequential in any one period, the regression coefficients on the distributed lags can be summed to obtain the *total* impact of an acquisition across time (Gujarati, 1988: 507). By using the variances and covariances of the individual lag coefficients from the regression output the variance of the summed coefficient can be calculated. The summed coefficient can then be used for hypothesis testing. For instance, the hypothesis that the total impact of acquisitions summed across all years is zero can be tested by computing the following t-statistic and checking whether it is statistically significant at the desired confidence level (Greene, 1993; Gujarati, 1988).

$$t = (\beta_{t-1} + \beta_{t-2} + \beta_{t-3} + \beta_{t-4}) \,/\, \sqrt{\text{Variance}\,(\beta_{t-1} + \beta_{t-2} + \beta_{t-3} + \beta_{t-4})}$$

where the β_{t-i}'s are the regression coefficients for the ith period lagged acquisition variable (Judge *et al.*, 1988). The variance for the summed coefficients can be computed using the following relation (Gujarati, 1988: 507):

$$\begin{aligned}\text{Variance}\,(\beta_{t-1} + \beta_{t-2} + \beta_{t-3} + \beta_{t-4}) &= [\text{Var}(\beta_{t-1}) + \text{Var}(\beta_{t-2}) \\ &+ \text{Var}(\beta_{t-3}) + \text{Var}(\beta_{t-4}) \qquad (2)\\ &+ 2\text{Cov}(\beta_{t-1}\beta_{t-2}) + 2\text{Cov}(\beta_{t-1}\beta_{t-3}) \\ &+ 2\text{Cov}(\beta_{t-1}\beta_{t-4}) + 2\text{Cov}(\beta_{t-2}\beta_{t-3}) \\ &+ 2\text{Cov}(\beta_{t-2}\beta_{t-4}) + 2\text{Cov}(\beta_{t-3}\beta_{t-4})]\end{aligned}$$

The conditioning vector X in Equation 1 helps us to control for alternative explanations. For instance, since an acquisition represents the absorption of one firm by another, a simple explanation for an increased postacquisition innovation output would simply be increased innovative inputs—the one postacquisition firm reflects the combined efforts of the two preacquisition firms. By including innovative inputs as time-varying covariates in the conditioning vector X, we can directly control for such effects. Other possible determinants of innovation outputs such as firm size, diversification, nationality, and time are also controlled for through this vector.

This specification does not account for unobserved heterogeneity, or the possibility that observationally equivalent firms may differ on unmeasured characteristics. For instance, firms may enter the sample with inherently different innovation generating capabilities. Such unobserved heterogeneity, if present and not controlled for, can cause estimation problems. First, it can lead to overdispersion in the data. For the Poisson distribution the variance is restricted to equal the mean. If this restriction is false and the data are overdispersed in that the variance exceeds the mean, the computed standard errors in a Poisson regression are understated. Second, unobserved firm effects can lead to serial correlation among the residuals of observations from the same firm. Under overdispersion or serial correlation, computed regression coefficients remain consistently estimated; however, the standard errors are inaccurate. Thus, hypothesis testing and inference can be invalidated. To address the possibility of unobserved heterogeneity we used the Presample Panel Poisson approach (Blundell, Griffith, and Van Reenen, 1995).

In the Presample approach, unobserved heterogeneity is modeled as an additional covariate in the basic Poisson model. The values of the dependent variable in the periods immediately preceding the study period are used to construct an instrumental variable. This instrumental variable serves as a 'fixed-effect' for the firms in the panel and helps to partial out unobservable differences across firms. Thus, presample information on the firms provides the basis for controlling for unobserved heterogeneity. In the context of the current research the Presample variable can be interpreted as a measure of the unobserved differences in knowledge stocks between the sample firms.

Although the presample approach can help in the reduction of overdispersion and serial correlation, a more complete treatment of these potential problems would be to use an estimation approach that accounts for any remaining overdispersion and serial correlation even after the inclusion of a presample variable. The Generalized Estimating Equations (GEE) methodology provides a direct approach to modeling longitudinal Poisson data with serial correlation in a regression context (Liang and Zeger, 1986). The GEE estimation procedure involves two stages. In the first stage of the procedure beta coefficients are estimated with the assumption of independence across observations. This process yields consistent estimates of the beta parameters and the residuals from this regression provide an estimate of the 'working correlations' between the errors of different observations. This working correlation matrix is then used as an input in a second regression. The beta coefficients and standard errors from this second regression provide consistent estimates of the underlying parameters while accounting for the observed correlation between observations. To ensure that all residual correlation was accounted for, we used the GEE procedure to estimate all models. Even for the GEE approach instead of using the model-based standard errors we used the more conservative (i.e., larger) empirical standard errors. This ensures that other potential misspecifications of the variance function, such as any residual overdispersion, are also accounted for.

Sample and data

We tested the hypotheses on a longitudinal data set comprising the acquisition and patenting activities of 72 leading firms from the global chemicals industry. Focusing on the largest firms of the industry was necessary to ensure the availability and reliability of data. Obtaining information on the key variables for smaller firms is extremely difficult. This focus on large firms is also consistent with prior research on acquisitions (Hitt *et al.*, 1991, 1996). We identified the 100 leading players in the chemicals industry from lists of the largest chemicals firms that are published annually by trade journals such as *Chemical Week* and *C&E News*. To avoid survivor bias, the selected sample was drawn from the lists at the beginning of the study period. In these published lists subsidiaries were often listed separately from parent firms. After combining subsidiaries with parent firms, a sample of 82 independent firms was identified for inclusion in the sample. However, for 10 firms data could not be reliably obtained and they were subsequently dropped from the analysis. The remaining firms include the key firms in the industry over the study period and comprise of 30 European, 26 American, and 16 Japanese firms. The panel is unbalanced as some of the firms were acquired by other firms or restructured in a fashion that made comparison difficult beyond a particular year. Even though the sample was focused on the largest firms in the chemicals industry the inclusion of 72 firms provides significant depth to the sample and ensures that there is considerable variety within the sample on the key variables of this study. For instance, the number of employees for firms in the sample varies from a minimum of 2300 to a maximum of more than 181,000. Similarly, the number of patents obtained yearly varies from 0 to 760. Financial figures and personnel data on these firms were obtained from Compustat, Worldscope, Japan Company Handbooks, Daiwa Institute Research Guides, and trade publications and company annual reports. For all firms, financial data were converted to constant (1985) U.S. dollars to ensure standardization within the sample. A full list of the sample firms is available from the authors.

The chemicals industry is an appropriate setting for several reasons. First, technology-based acquisitions have been a significant feature of this industry (*Chemical Week*, 1983; Gibson, 1985). Second, patents are generally regarded to be effective, and used widely and consistently in the chemicals industry (Levin *et al.*, 1987; Arundel and Kabla, 1998). For the firms in the sample we obtained yearly patent counts from 1975 to 1992 and acquisition and firm attribute data for the years 1980 to 1991. The need to use lagged relationships between patent counts and the other variables and to construct a control for unobserved heterogeneity reduced the final panel for regression analysis to 9 years. We describe the data collection and coding procedures for the three sets of variables in some detail below.

We used U.S. patent data for all firms, including the foreign firms in the sample. This was necessary to maintain consistency, reliability, and comparability, as patenting systems across nations differ in their application of standards, system of granting patents, and value of protection granted. The United States represents one of the largest markets for chemicals, and firms desirous of commercializing their inventions typically patent in the United States if they patent anywhere. Studies by Dosi, Pavitt and Suete (1990) and Basberg (1983) show empirically that U.S. patent data provide a good measure of foreign firms' innovativeness. Prior research using patent data on international samples has also followed this strategy of using U.S. patent data for international firms (e.g., Stuart and Podolny, 1996; Patel and Pavitt, 1997).

Data on acquisitions were obtained through detailed archival research on the chemicals sector. Three main types of data sources were used to identify acquisition activity and to collect data on acquisition transactions: (1) commercial data bases, including general business news media such as the Dow Jones News Retrieval Text Index, and chemicals sector-specific data bases such as Metadex, (2) general business print media such as the Frost and Sullivan Predicasts Index (United States, International, and Europe), *Mergers and Acquisitions Journal* and Moody's Manuals, and industry-specific publications such as *Chemical Week* and *Plastics Technology*, and, (3) government publications and consultant reports for the chemicals industry. We were able to identify 1287 acquisition announcements for the sample firms over the period of 1980 to 1991.

To identify the technological acquisitions within this larger sample two approaches were used. First, we obtained detailed news stories associated with each acquisition announcement. We were able to obtain news stories providing details for 516 of the 1287 acquisitions identified for the sample firms. For the remaining acquisitions no further details, or inadequate details, were available. Second, we searched the U.S. Patents Data Base to determine if the acquired firms had obtained any patents in the 5 years preceding the acquisition. 165 of the acquired firms had obtained patents during the 5 years preceding their acquisition. For all subsequent analyses we retained only those acquisitions for which we were able to find either corroborating news stories or patenting activity (534 acquisitions in total). Acquisitions for which we were able to obtain no further information were omitted. The paucity of information on these acquisitions suggests that these acquisitions were very small or unimportant. Therefore, our analysis is based on the 534 acquisitions for which we have relatively complete information.

We used two criteria to distinguish technological acquisitions from all other acquisitions. First, we examined the news stories to establish if the acquiring firm reported technology as a motivating factor for the acquisition or if technology was a part of the transferred assets. We classified the acquisition as technological if either of these conditions was met. Second, we classified the acquisition as technological if the acquired firm had any patenting activity in the 5 years preceding the acquisition. Of the 534 acquisitions on which we had information, 283 met at least one of the two above criteria and were classified as technological acquisitions. The remaining 251 acquisitions were classified as nontechnological.

This classification scheme reflects a fairly inclusive definition of technological acquisitions. Firms need not have patented to be classified as technology acquisitions. Further, acquired firms obtaining even a single patent in the 5 years prior to the acquisition are classified as technological acquisitions.

This classification scheme provides two benefits. First, it uses two indicators to identify technological acquisitions and therefore enables more complete identification of technological acquisitions than either indicator by itself would. For instance, our patent-based measures cannot be computed if only a part of a firm is acquired, rather than the complete entity, or if the technology has not been patented at all. In such circumstances the news story could provide an indication of whether the transaction entailed technology or not. Similarly, if the acquisition was motivated by multiple factors of which technology was not necessarily the one mentioned in the news story, the patents measure provides an indicator of whether technology was involved. Thus, using the input from the news stories supplements our patent-based measures.

Second, using this scheme of classification makes our statistical tests more conservative. With this scheme we are likely to capture any acquisition that includes a technological component. Further, we are more likely to err in the direction of defining acquisitions as technological even when they have a relatively small technology component. If such misclassifications occur, we reduce our likelihood of finding a positive impact of technological acquisitions on the innovation performance of acquiring firms.

Finally, we need to select a time period or window for measuring a firm's knowledge base. At one extreme only the current year's patents could be considered relevant. At another extreme any patent obtained by the firm in the past could be included in computing its current knowledge base. Prior research suggests that knowledge capital depreciates sharply, losing significant value within 5 years (Griliches, 1979). Although the depreciation rate for knowledge capital is likely to vary across industries, a boundary of 5 or 6 years seems reasonable and has been used by other researchers (Podolny and Stuart, 1995; Henderson and Cockburn, 1996). In this research we use the patents obtained by a firm in the preceding 5 years to compute our knowledge base measures. We also computed some of the measures using patents for the preceding 6 years. These measures were highly correlated with the 5-year measures, suggesting that the construct is not unduly influenced by changes in the time period used to compute it.

Variable definitions and operationalization

Dependent variable

Patents Innovation output, the dependent variable, is measured through the patenting frequency of firms, that is, the number of successful patent applications by a firm in a given year. Patents have both significant strengths and weaknesses as measures of innovation output. First, patents are directly related to inventiveness: they are granted only for 'nonobvious' improvements or solutions with discernible utility (Walker, 1995). Second, they represent an externally validated measure of *technological* novelty (Griliches, 1990). Third, they confer property rights upon the assignee and therefore have *economic* significance (Kamien and Schwartz, 1982: 49; Scherer and Ross, 1990: 621).

Patents also correlate well with other measures of innovative output. Empirical studies find that patents are closely related to measures such as new products (Comanor and Scherer, 1969), innovation and invention counts (Achilladelis, Schwarzkopf and Cines, 1987), and sales growth (Scherer, 1965). Expert ratings of corporate technological strength are also highly correlated with the number of patents held by corporations (Narin, Noma, and Perry, 1987). Further, surveys of patent holders indicate that the rate of utilization of patents is reasonably high, with estimates indicating that between 41 percent and 55 percent of all patents granted are put to commercial use for at least a limited time (Griliches, 1990). Similarly, about 50 percent of all patents granted are still being renewed and a renewal fee is being paid 10 years after the patents had originally been applied for (Griliches, 1990; Schankerman and Pakes, 1986). Given a nonnegligible renewal fee, this indicates a significant usefulness for the majority of patents for a significant time period.

However, the use of patents as a measure of innovative output also has limitations. Some inventions are not patentable, others are not patented, and the inventions that are patented differ greatly in economic value (Cohen and Levin, 1989; Griliches, 1990; Trajtenberg, 1990). Research, and the logic of appropriability, indicate that the degree to which the first two of these factors are a problem varies significantly across industries (Cohen and Levin 1989; Levin *et al.*, 1987). Limiting the study to a single industrial sector or a few closely related sectors minimizes such problems as the factors that affect patenting propensity are likely to be stable within such a context (Basberg, 1987; Cohen and Levin, 1989; Griliches, 1990).

We measure Patents$_{it}$, as the number of *successful* patent applications, or granted patents, for the acquiring firm *i* in year *t*. The granted patent carries the date of the original application. We use this date to assign a granted patent to the particular year when it was originally applied for. This procedure permits consistency in the treatment of all patents and controls for differences in delays that may occur in granting patents after the application is filed (Trajtenberg, 1990). Note that the patent count for the dependent variable is based on the patents of the acquiring firm obtained 1–4 years *after* the acquisition in all cases. These patents are therefore different from the patents on which the independent variables are based. The independent variables described below are based on patents obtained by the acquired and acquiring firms, respectively, in the 5 years *before* the acquisition.

Independent variables

Number of nontechnological acquisitions As noted earlier, acquisitions were coded as technological acquisitions if either of the following two criteria are met: first, if the acquiring firm reported technology as a motivating factor for the acquisition or if technology was reported as a part of the transferred assets of the acquired firm; second, if the acquired firm had any patenting activity in the 5 years preceding the acquisition. Acquisitions that did not meet either of the above criteria were coded as nontechnological acquisitions. We used four lagged versions of this and all other acquisition related variables listed below.

Absolute size of acquired knowledge base To obtain this variable we used the following procedure: for each acquiring firm for each year, we prepared a list of the patents its acquisitions had obtained in the preceding 5 years. These patents were then combined with the patents cited by them. Thereafter, all duplicates were removed to ensure that a patent number appeared only once on this list. The acquired knowledge base was then computed as the number of patents (i.e., knowledge elements) on this list.

Relative size of acquired knowledge base This variable was obtained by dividing *Absolute size of acquired knowledge base* by the size of the acquiring firm's knowledge base. The size of the acquiring firm's knowledge base was computed using the same procedure as the size of the acquired firm's knowledge base (see above). In a few cases the acquired knowledge base was larger than the acquiring knowledge base. In these cases we used the larger number as the denominator. Since our theoretical mechanism is concerned with the relative *proportion* of the merged firms' resources that are likely to be occupied with integrative rather than inventive activity, a number greater than 1 is not meaningful.

Relatedness of acquired knowledge base To measure the relatedness of the acquired knowledge base, the following procedure was followed. First, the list of patent numbers that appeared in both the acquired firm's knowledge base and in the acquiring firm's knowledge base was prepared. Then, the number of elements on this list was divided by *Absolute size of acquired knowledge base*.

Number of technological acquisitions where patents unavailable This is the number of acquisitions for which news stories indicated that technology was a component of the transferred assets but where no patents could be identified with the acquisition. This would occur if either the acquired unit had obtained no patents or if the acquired unit was a part of a larger parent firm and patents were not assigned separately to the acquired unit and therefore could not be separated from the parent firm's patents.

Controls

We included several control variables in the models. These control variables include yearly R&D expenditures (*R&D*), firm size as measured by natural log of number of employees (*Logemployees*), firm diversification as measured by entropy (*Diversification*), and a measure of national cultural distance between the acquired and acquiring firms (*Foreign acquisitions*). The following formula was used to calculate the *Diversification* measure: Entropy $= \Sigma P_j \times \ln(1/P_j)$, where P_j is defined as the percentage of firm sales in segment j and $\ln(1/P_j)$ is the weight for each segment j (Palepu, 1985). *Foreign acquisitions* was computed as

$$\text{Foreign\_acquisitions} = \sum_{i=1}^{4} \{(I_{ij}-I_{iu})^2 / V_i\} / 4 \qquad (3)$$

where I_i stands for the index of the ith cultural dimension, j and u are subscripts indicating the countries j and u, and V_i is the variance of the index of the ith dimension (Hofstede, 1980). The index thus indicates the cultural distance between the acquirer's country (j) and the acquired firm's country (u) (Kogut and Singh, 1988). We anticipate that foreign acquisitions might be more difficult to integrate than domestic acquisitions. Finally, in all models we included the firm heterogeneity control variable *Presample patents* (the sum of patents obtained by a firm in the 3 years prior to the firm's entry into the sample) and dummy variables for acquirer nationality and calendar year.

RESULTS

Table 1 provides descriptive statistics and correlations. The table indicates the diversity of firms included in the sample. Even though the sample involves the prominent players in the industry, there is considerable variance on all the key variables such as *Patents*, *R&D*, *Logemployees*, and the acquisition variables. The variables reflecting the hypothesized effects are not very highly correlated among themselves or with the control variables. However, the correlations between some of the control variables are high, notably the correlation between *R&D* and *Logemployees* (0.72), and the correlation of the firm fixed-effect variable *Presample patents* with *R&D* (0.89) and *Logemployees* (0.72). Robustness tests (reported at the end of this section), however, indicate that the results on the hypothesized effects were strong and unaffected by these high correlations between some of the control variables.

Table 2 provides results for all models using GEE Poisson estimators (reported with empirical standard errors). The variables reflecting the hypothesized effects were entered into the regression individually and likelihood ratio tests are reported for all models. Model 1 in Table 2 presents the base model with firm- and acquisition-related control variables. Models 2–6 include the *Number of nontechnological acquisitions*, *Absolute size of acquired knowledge base*, *Relative size of acquired knowledge base*, *Relatedness of acquired knowledge base* and *Relatedness of acquired knowledge base*^{2} variables entered successively. We use the full model to discuss the results of the hypothesis tests. The summed coefficients and the associated standard errors for the lagged acquisition variables for these models are given at the bottom of the table.

In Hypothesis 1 we predicted a negative or nonsignificant relationship between the number of nontechnological acquisitions conducted in a year and the subsequent innovation output of the acquiring firm. The coefficients of *Number of non-technological acquisitions* are nonsignificant for all four periods individually. The summed coefficient, which represents the total effect of acquisitions across the 4 years, is not statistically significantly different from zero. Thus, we do not find an appreciable impact of acquisitions without a technological component on the innovation output of the acquirer for the four periods following the acquisition.

The coefficients of the four *Absolute size of acquired knowledge base* variables in Model 6 in Table 2 are positive and significant, supporting Hypothesis 2. The summed coefficient reflecting the total impact of the acquisition is also positive and significant. However, as the summed coefficient indicates (0.0004), the absolute magnitude of this effect is low. A one-unit increase in the knowledge base of the acquired firm leads to a 0.04 percent increase in the acquirer's innovation

Table 1. Means, standard deviations, minimum and maximum values and bivariate correlations for all variables

Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1 *Patients*$_{t}$	93.90	137.65	0.00	760.00																																		
2 *No. of nontechnological acquisitions*$_{t-1}$	0.35	0.79	0.00	6.00	0.12																																	
3 *No. of nontechnological acquisitions*$_{t-2}$	0.34	0.78	0.00	6.00	0.12	0.26																																
4 *No. of nontechnological acquisitions*$_{t-3}$	0.29	0.68	0.00	5.00	0.11	0.29	0.23																															
5 *No. of nontechnological acquisitions*$_{t-4}$	0.25	0.69	0.00	7.00	0.12	0.21	0.29	0.30																														
6 *Absolute size of acquired knowledge base*$_{t-1}$	26.08	275.94	0.00	6227.00	0.13	0.07	−0.03	0.01	−0.02																													
7 *Absolute size of acquired knowledge base*$_{t-2}$	34.59	332.94	0.00	6227.00	0.15	−0.03	0.05	−0.03	0.00	0.02																												
8 *Absolute size of acquired knowledge base*$_{t-3}$	34.83	338.80	0.00	6227.00	0.18	−0.02	−0.03	0.01	−0.03	0.03	0.01																											
9 *Absolute size of acquired knowledge base*$_{t-4}$	33.20	337.48	0.00	6227.00	0.19	0.00	−0.02	−0.03	0.02	0.51	0.03	0.01																										
10 *Relative size of acquired knowledge base*$_{t-1}$	0.02	0.08	0.00	0.90	−0.04	0.12	0.00	0.00	−0.05	0.44	−0.01	0.00	0.16																									
11 *Relative size of acquired knowledge base*$_{t-2}$	0.02	0.09	0.00	0.90	−0.01	−0.01	0.12	−0.01	−0.01	0.00	0.56	−0.01	0.00	−0.02																								
12 *Relative size of acquired knowledge base*$_{t-3}$	0.02	0.09	0.00	0.90	0.01	0.04	0.00	0.09	0.00	0.04	0.00	0.55	−0.01	0.05	−0.02																							
13 *Relative size of acquired knowledge base*$_{t-4}$	0.02	0.08	0.00	0.90	0.02	−0.02	0.03	0.03	0.05	0.37	0.03	0.00	0.56	0.12	0.05	0.00																						
14 *Relatedness of acquired knowledge base*$_{t-1}$	0.01	0.06	0.00	1.00	0.03	−0.02	0.02	−0.03	−0.03	0.04	0.00	−0.01	0.01	0.09	−0.01	−0.02	0.27																					
15 *Relatedness of acquired knowledge base*$_{t-2}$	0.01	0.06	0.00	1.00	0.04	0.00	−0.01	0.02	−0.03	−0.01	0.03	0.00	−0.01	0.00	0.08	0.00	−0.01	−0.02																				
16 *Relatedness of acquired knowledge base*$_{t-3}$	0.01	0.06	0.00	1.00	0.05	0.03	0.00	−0.01	0.03	0.07	−0.01	0.03	0.00	0.07	0.00	0.07	0.00	−0.02	−0.02																			
17 *Relatedness of acquired knowledge base*$_{t-4}$	0.01	0.06	0.00	1.00	0.06	0.02	0.03	0.00	−0.01	0.09	0.06	−0.01	0.03	0.02	0.06	0.00	0.07	0.04	−0.01	−0.01																		
18 *Relatedness of acquired knowledge base*$_{t-1}^{2}$	0.00	0.05	0.00	1.00	−0.01	−0.03	0.02	−0.03	−0.03	0.01	−0.01	0.00	0.01	0.04	−0.01	−0.01	0.36	0.92	−0.01	−0.01	0.00																	
19 *Relatedness of acquired knowledge base*$_{t-2}^{2}$	0.00	0.05	0.00	1.00	0.00	−0.02	−0.03	0.02	−0.03	0.00	0.00	−0.01	0.00	0.01	0.03	−0.01	0.00	−0.01	0.92	−0.01	−0.01	−0.01																

Table 1. Continued

Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
20 *Relatedness of acquired knowledge base*$_{t-3}{}^{2}$	0.00	0.05	0.00	1.00	0.00	0.00	−0.02	−0.03	0.03	0.02	0.00	0.00	−0.01	0.03	0.01	0.03	−0.01	−0.01	−0.01	0.92	−0.01	−0.01	−0.01															
21 *Relatedness of acquired knowledge base*$_{t-4}{}^{2}$	0.00	0.05	0.00	1.00	0.01	−0.01	0.00	−0.02	−0.03	0.05	0.02	0.00	0.00	0.01	0.03	0.01	0.04	0.02	−0.01	−0.01	0.93	0.00	−0.01	−0.01														
22 *No. of technological acquisitions where patents unavailable*$_{t-1}$	0.17	0.47	0.00	3.00	0.19	0.22	0.16	0.17	0.20	0.03	−0.03	−0.02	0.02	0.06	−0.04	0.00	−0.02	0.01	0.01	0.03	0.00	−0.01	−0.02	0.00	−0.02													
23 *No. of technological acquisitions where patents unavailable*$_{t-2}$	0.16	0.46	0.00	3.00	0.21	0.10	0.23	0.18	0.17	−0.01	0.01	−0.03	−0.02	0.00	0.05	−0.03	0.01	−0.03	0.01	0.02	0.04	−0.03	−0.01	−0.01	0.00	0.28												
24 *No. of technological acquisitions where patents unavailable*$_{t-3}$	0.14	0.43	0.00	3.00	0.22	0.15	0.11	0.23	0.22	0.01	−0.01	−0.01	−0.03	0.00	−0.02	0.02	−0.02	0.05	−0.03	0.02	0.00	0.03	−0.02	−0.01	−0.02	0.19	0.31											
25 *No. of technological acquisitions where patents unavailable*$_{t-4}$	0.13	0.41	0.00	3.00	0.19	0.15	0.15	0.08	0.20	−0.02	0.00	−0.02	−0.02	−0.02	0.00	−0.02	−0.01	0.02	0.06	−0.03	0.00	−0.01	0.03	−0.02	−0.01	0.14	0.21	0.31										
26 *Foreign acquisitions*$_{t-1}$	0.20	0.86	0.00	14.66	0.02	0.23	0.06	0.07	0.04	0.15	−0.02	0.00	−0.01	0.33	−0.03	0.11	0.01	0.12	−0.02	0.17	−0.01	0.08	−0.02	0.09	−0.01	0.39	0.14	0.12	0.04									
27 *Foreign acquisitions*$_{t-2}$	0.19	0.85	0.00	14.66	0.03	0.06	0.24	0.05	0.08	0.00	0.12	−0.01	0.00	0.01	0.29	−0.03	0.12	0.01	0.13	−0.02	0.19	0.00	0.08	−0.01	0.09	0.10	0.40	0.16	0.14	0.15								
28 *Foreign acquisitions*$_{t-3}$	0.15	0.60	0.00	6.86	0.04	0.24	0.10	0.15	0.10	0.08	0.00	0.01	−0.01	0.11	0.00	0.15	−0.02	−0.01	0.02	0.19	−0.01	−0.02	0.01	0.12	−0.02	0.18	0.17	0.41	0.22	0.42	0.23							
29 *Foreign acquisitions*$_{t-4}$	0.15	0.69	0.00	8.97	0.03	0.10	0.21	0.07	0.11	0.01	0.06	−0.01	0.01	0.01	0.08	−0.01	0.16	−0.01	0.00	0.01	0.17	−0.01	−0.01	0.00	0.10	0.05	0.15	0.14	0.43	0.15	0.37	0.25						
30 *R&D*$_{t-1}$	19.32	30.24	0.23	161.25	0.89	0.18	0.19	0.16	0.16	0.08	0.09	0.10	0.11	−0.04	−0.02	−0.01	−0.01	0.03	0.05	0.07	0.07	0.00	0.00	0.01	0.02	0.24	0.30	0.30	0.26	0.07	0.11	0.15	0.12					
31 *Logemployees*$_{t-1}$	2.76	1.14	0.83	5.20	0.70	0.31	0.31	0.28	0.28	0.13	0.15	0.15	0.15	0.00	0.03	0.05	0.04	0.05	0.05	0.06	0.05	0.01	0.01	0.01	0.00	0.29	0.28	0.28	0.24	0.13	0.14	0.18	0.17	0.72				
32 *Diversification/Entropy*$_{t-1}$	0.53	0.41	0.00	1.60	0.04	0.10	0.08	0.07	0.06	0.10	0.12	0.11	0.10	0.05	0.09	0.10	0.10	0.01	0.01	0.00	0.01	0.02	0.02	0.01	0.02	−0.03	−0.07	−0.08	−0.12	0.01	0.00	−0.06	−0.08	−0.05	0.14			
33 *U.S.A.*	0.35	0.48	0.00	1.00	0.10	−0.04	−0.04	0.00	0.02	0.04	0.07	0.09	0.09	−0.01	0.03	0.04	0.08	0.08	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.05	0.04	0.07	0.08	−0.13	−0.12	−0.12	−0.11	−0.02	0.08	0.13		
34 *Japan*	0.24	0.43	0.00	1.00	−0.19	−0.24	−0.23	−0.22	−0.20	−0.04	−0.05	−0.05	−0.05	−0.08	−0.09	−0.09	−0.09	−0.07	−0.07	−0.07	−0.06	−0.05	−0.04	−0.04	−0.04	−0.17	−0.17	−0.15	−0.16	−0.05	−0.07	−0.07	−0.07	−0.21	−0.53	−0.10	−0.42	
35 *Presample patents*$_{t-1}$	2.28	3.26	0.01	15.80	0.94	0.11	0.12	0.09	0.10	0.07	0.08	0.11	0.11	−0.07	−0.05	−0.03	−0.03	0.05	0.05	0.05	0.05	0.01	0.01	0.01	0.01	0.20	0.21	0.21	0.18	0.00	0.02	0.05	0.04	0.89	0.72	0.02	0.10	−0.20

Table 2. GEE presample Poisson regression with distributed lag analysis predicting patents$_t$ variable

Variable	1	2	3	4	5	6
Intercept	1.906*** [0.333]	1.916*** [0.334]	1.994*** [0.296]	2.055*** [0.293]	2.041*** [0.295]	2.048*** [0.292]
No. of nontechnological acquisitions$_{t-1}$		0.004 [0.017]	0.009 [0.017]	0.009 [0.016]	0.008 [0.016]	0.004 [0.017]
No. of nontechnological acquisitions$_{t-2}$		–0.002 [0.018]	–0.0003 [0.017]	0.004 [0.016]	0.005 [0.016]	0.004 [0.016]
No. of nontechnological acquisitions$_{t-3}$		–0.001 [0.023]	–0.006 [0.023]	–0.002 [0.023]	–0.003 [0.023]	–0.002 [0.024]
No. of nontechnological acquisitions$_{t-4}$		–0.010 [0.014]	–0.012 [0.014]	–0.008 [0.013]	–0.010 [0.013]	–0.008 [0.012]
Absolute size of acquired knowledge base$_{t-1}$			0.0001** [0.00004]	0.0001*** [0.00002]	0.0001*** [0.00002]	0.0001*** [0.00003]
Absolute size of acquired knowledge base$_{t-2}$			0.0001*** [0.00003]	0.0001*** [0.00002]	0.0001*** [0.00002]	0.0001*** [0.00002]
Absolute size of acquired knowledge base$_{t-3}$			0.0001*** [0.00002]	0.0001*** [0.00002]	0.0001*** [0.00002]	0.0002*** [0.00002]
Absolute size of acquired knowledge base$_{t-4}$			0.0000 [0.0000]	0.0001** [0.00004]	0.0001** [0.00004]	0.0000* [0.0001]
Relative size of acquired knowledge base$_{t-1}$				–0.393** [0.165]	–0.387** [0.167]	–0.348* [0.156]
Relative size of acquired knowledge base$_{t-2}$				–0.447*** [0.144]	–0.442*** [0.142]	–0.455*** [0.144]
Relative size of acquired knowledge base$_{t-3}$				–0.388*** [0.125]	–0.405*** [0.125]	–0.488*** [0.121]
Relative size of acquired knowledge base$_{t-4}$				–0.479** [0.196]	–0.430* [0.198]	–0.369* [0.209]
Relatedness of acquired knowledge base$_{t-1}$					–0.207 [0.176]	0.221 [0.558]
Relatedness of acquired knowledge base$_{t-2}$					0.002 [0.112]	0.821* [0.384]
Relatedness of acquired knowledge base$_{t-3}$					0.158 [0.111]	0.847* [0.371]
Relatedness of acquired knowledge base$_{t-4}$					0.151 [0.121]	0.836** [0.335]
Relatedness of acquired knowledge base$^2_{t-1}$						–0.820 [0.911]

Table 2. Continued

Variable	1	2	3	4	5	6
Relatedness of acquired knowledge base$^2_{t-2}$						–1.580** [0.572]
Relatedness of acquired knowledge base$^2_{t-3}$						–1.301* [0.572]
Relatedness of acquired knowledge base$^2_{t-4}$						–1.251** [0.501]
No. of technological acquisitions where patents unavailable$_{t-1}$		0.023 [0.026]	0.034 [0.024]	0.016 [0.023]	0.018 [0.023]	0.009 [0.024]
No. of technological acquisitions where patents unavailable$_{t-2}$		0.011 [0.024]	0.025 [0.022]	0.016 [0.021]	0.016 [0.021]	0.014 [0.022]
No. of technological acquisitions where patents unavailable$_{t-3}$		0.039 [0.030]	0.053* [0.027]	0.043 [0.026]	0.047 [0.025]	0.045 [0.025]
No. of technological acquisitions where patents unavailable$_{t-4}$		0.063* [0.020]	0.068* [0.027]	0.066* [0.026]	0.073** [0.026]	0.077** [0.027]
Foreign acquisitions$_{t-1}$	0.034** [0.012]	0.031 [0.016]	0.026 [0.017]	0.035 [0.019]	0.038* [0.017]	0.040* [0.017]
Foreign acquisitions$_{t-2}$	0.020* [0.010]	0.019 [0.013]	0.014 [0.012]	0.023 [0.015]	0.022 [0.015]	0.024 [0.015]
Foreign acquisitions$_{t-3}$	–0.020 [0.013]	–0.042* [0.017]	–0.051** [0.016]	–0.042* [0.017]	–0.046** [0.016]	–0.043* [0.017]
Foreign acquisitions$_{t-4}$	0.009 [0.013]	–0.008 [0.015]	–0.010 [0.015]	–0.004 [0.017]	–0.008 [0.017]	–0.011 [0.017]
R&D$_{t-1}$	–0.0004 [0.001]	–0.001 [0.002]	–0.001 [0.002]	–0.001 [0.002]	–0.001 [0.001]	–0.001 [0.001]
Logemployees$_{t-1}$	0.554*** [0.105]	0.553*** [0.109]	0.534*** [0.099]	0.517*** [0.097]	0.522*** [0.097]	0.516*** [0.096]
Diversification/ Entropy$_{t-1}$	–0.176* [0.076]	–0.187* [0.083]	–0.217* [0.085]	–0.180* [0.080]	–0.183* [0.080]	–0.174* [0.076]
US firm	0.553*** [0.128]	0.549*** [0.130]	0.526*** [0.120]	0.509*** [0.118]	0.507*** [0.117]	0.514*** [0.114]
Japanese firm	0.997*** [0.233]	1.006*** [0.229]	0.991*** [0.219]	0.942*** [0.217]	0.950*** [0.217]	0.951*** [0.216]
Presample patents$_{t-1}$	0.135*** [0.022]	0.137*** [0.024]	0.145*** [0.024]	0.142*** [0.023]	0.143*** [0.023]	0.142*** [0.022]

output. If we consider a hypothetical acquisition in which the acquired firm has a knowledge base with 50 elements (50 elements corresponds approximately to a firm with 10 owned patents plus 40 cited patents) then the above coefficient suggests that this acquisition should lead to a 2 percent increase in innovation output ($0.0004 \times 50 = 0.02$) for the acquiring firm after the acquisition, other things being equal.

In Hypothesis 3, a negative relationship was proposed between the relative size of an acquisition and the subsequent innovation performance of the acquiring firm. This prediction was also borne out. Specifically, the individual and

Table 2. Continued

Variable	1	2	3	4	5	6
N	598	598	598	598	598	598
Pearson chi sq./d.f.	10570/579	10491/571	9923/567	9454/563	9448/559	9280/555
–2 log-likelihood vis à vis the preceding model		158***	1136***	938***	12***	336***
Summed coefficients (Model 6)						
No. of nontechnological acquisitions						–0.001 [0.054]
Absolute size of acquired knowledge base						0.0004** [0.000]
Relative size of acquired knowledge base						–1.660** [0.661]
Relatedness of acquired knowledge base						2.725** [1.332]
Relatedness of acquired knowledge base^2						–4.951** [2.020]
No. of technological acquisitions where patents unavailable						0.145* [0.081]
Foreign acquisitions						0.011 [0.049]

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$ (one-tailed tests for hypothesized variables, two-tailed tests for controls)
The table gives parameter estimates; standard errors are in brackets. Year dummies are included, but not shown.

summed coefficients for *Relative size of acquired knowledge base* are negative, indicating that acquiring firms that are large relative to the acquirer leads to a decline in postacquisition innovation output for the acquirer. We also find support for Hypothesis 4. As shown in Model 6 of Table 2, the coefficients for *Relatedness of acquired knowledge base* are positive, and that for its squared term, *Relatedness of acquired knowledge base*^{2}, are negative. These findings support the argument that the relatedness of acquisitions has a curvilinear impact on the subsequent innovation output of acquiring firms. The summed coefficients at the bottom of Table 2 support the same results.

Among the control variables, the coefficients on *Number of technological acquisitions where patents unavailable* for the 1-year, 2-year, and 3-year lags are positive but not significant. However, the 4-year lag is positive and significant. The summed coefficient is positive and significant. Thus, technological acquisitions for which we were unable to identify patents also improve postacquisition innovation output.

Foreign acquisitions, which represents the cultural distance between acquired and acquiring firms, has a nonsignificant impact on innovation output. Although the 1-year and 3-year lagged variables are marginally significant but in opposite directions (positive and negative, respectively), the summed coefficient is positive but not statistically significant (Table 2). Although these results are not conclusive it appears that, on balance, foreign acquisitions neither help nor hurt innovation output. This finding is consistent with recent research on international acquisitions, which finds that acquisitions in which the acquirer and the acquired are from different countries do not result in greater postacquisition conflict, and, in fact, often lead to superior postacquisition performance (Weber, Shenkar, and Raveh, 1996; Very *et al.*, 1997). Nevertheless, further research is required to understand this issue more completely.

Logemployees, the control measuring the size of the acquirer, was found to be positively associated with patenting frequency. *Diversification* is negatively associated with patenting frequency. Prior results on the impact of diversification on innovative activity have been mixed; studies find that diversification has both a positive and a negative impact on innovation (Cohen and Levin, 1989). Diversification can either encourage innovation by providing a stimulus of multiple knowledge bases within a single firm and by leading to cross-fertilization of ideas, but it can also imply a loss of focus in a given technological area as research efforts are spread in multiple directions. The results of this research support the latter interpretation.

The *Presample patents* variable and several of the year dummies (not reported) were also significant in all the models. This indicates that it was important to control for unobserved firm effects as well as period effects in these data. The Year dummies for 1983–86 were negative and significant, while all the other year dummies were nonsignificant, relative to the omitted category—1991. These results indicate that patenting had significantly increased for this set of firms in the later years (1987–91), relative to the earlier years (1983–86). The nation dummy variables reflecting acquirer nationality, Japanese and U.S., were also positive and significant, indicating that Japanese and U.S. firms were likely to obtain more patents than European firms.

Sensitivity analyses

We also ran several sensitivity tests to check the robustness of the results. We reconstructed all the knowledge base measures after separating the patents obtained by a firm (Own Patents) from the patents cited by the firm (Cited Patents), and ran two distinct sets of models. In the first set we used knowledge-based measures for acquired and acquiring firms based on only the Own Patents of the firm (i.e., we excluded Cited Patents). In the second set we computed all knowledge-based measures for acquired and acquiring firms based on only the Cited Patents of the firms (i.e., we excluded Own Patents). The results of these analyses are presented in Table 3. In the interest of brevity, we only report the summed coefficients and associated *t*-tests for the models (the full regression table is available from the authors).

Table 3. GEE presample Poisson regression predicting patents$_t$. Own-cited patents measures. Summary of the summed coefficient results for all lagged variables

Variable	Own patents 1	Cited patents 2
No. of nontechnological acquisitions	–0.007 [0.057]	0.0006 [0.054]
Absolute size of acquired knowledge base (Own patents)	0.002*** [0.001]	
Relative size of acquired knowledge base (Own patents)	–1.632* [0.708]	
Relatedness of acquired knowledge base (Own patents)	2.411 [3.562]	
Relatedness of acquired knowledge base^2 *(Own patents)*	–3.568 [7.533]	
Absolute size of acquired knowledge base (Cited patents)		0.0004*** [0.000]
Relative size of acquired knowledge base (Cited patents)		–1.653*** [0.465]
Relatedness of acquired knowledge base (Cited patents)		2.752* [1.266]
Relatedness of acquired knowledge base^2 *(Cited patents)*		–4.759** [1.865]
No. of technological acquisitions where patents unavailable	0.196* [0.083]	0.141 [0.081]
Foreign acquisitions	–0.003 [0.003]	0.011 [0.048]

Reported coefficient estimates are the sum of the four lagged coefficients (β_{t-1}, β_{t-2}, β_{t-3}, β_{t-4}) for each variable.
$*p < 0.05$; $**p < 0.01$; $***p < 0.001$ (one-tailed tests for hypothesized variables, two-tailed tests for controls)

The summed coefficients in Table 3 indicate that with knowledge base measures based only on Own Patents (Model 1), the hypotheses (2 and 3) on *absolute size* of acquired firm and *relative size* of acquired firm were strongly supported. However, the coefficients for the *relatedness* hypothesis (4) carried the right signs (+ for relatedness and − for its square term), but they were statistically nonsignificant. In the analysis based on Cited Patents only (Model 2) all hypotheses (2, 3, and 4) were strongly supported. Thus, using only patents, or only citations to measure knowledge bases, provides rather similar results to using both patents and citations for the absolute size and relative size effects. However, in terms of measuring relatedness, the patents-only measures do not appear to capture relatedness as well as the citations-based measures. A comparison of the results in Table 3 (based on Own Patents or Cited Patents taken individually) with the results in Table 2 (based on combining Own and Cited patents to provide a single measure of knowledge elements), however, suggests that the relatedness measure based on both own and cited patents collectively is more predictive than the measures based on either Own Patents or Cited Patents only.

In the results discussed above we used the Presample Patents variable as a measure of unobserved differences in the knowledge bases of firms. The patent production function literature provides several alternate approaches to construct indices, reflecting differences in firms' knowledge stocks (Griliches, 1984; Hall *et al.*, 1988; Henderson and Cockburn, 1996). We constructed several such indices using different assumptions and input data. First, we used capitalized historical R&D expenditures to construct a knowledge stock index (Hall *et al.*, 1988).[2] Second, we constructed an index based on the moving average sum of R&D expenditures for the previous *n* years. We used a depreciation rate of 0.20 (consistent with Henderson and Cockburn, 1996, and other studies in this tradition) for the first approach and n = 5 years for the second approach, and estimated models using these indices in lieu of the R&D variable. We also computed the knowledge stock index using cumulative lagged depreciated patent stocks rather than cumulated lagged depreciated R&D, and used this as a control variable in our regression models in place of the Presample Patents measure. In additional estimation we used the one period lagged values of the dependent variable in lieu of the presample variable. The results for all these approaches (available from the authors) are very similar to the earlier reported results.

As noted earlier, the correlations between the three control variables, *R&D*, *Logemployees* and *Presample patents* were high. Although this high collinearity does not bias coefficient estimates, it can affect the stability of the estimated coefficients. Consequently, omitting even a few observations can change the sign or the significance of the affected variables (Greene, 1993). To ensure that our results were robust, we drew 50 random samples of 90 percent of the observations and estimated the full model for each of these samples. The results of this sensitivity analysis indicated that the results of our hypothesis testing were robust.

DISCUSSION

The results of the study indicate support for our theoretical predictions. Specifically, separating nontechnological acquisitions from technological acquisitions and distinguishing between technological acquisitions on the basis of the absolute size, relative size, and relatedness of the knowledge bases of the acquired firm helps in predicting postacquisition innovation output. We do not find any statistically significant impact of nontechnological acquisitions on subsequent innovation output. Within technological acquisitions, absolute size of the acquired knowledge base has a positive impact on innovation output, while relative size of the acquired knowledge base reduces innovation output. The relatedness of acquired and acquiring knowledge bases has a nonlinear impact on innovation output, with acquisition of firms with high levels of relatedness and unrelatedness both proving inferior to acquiring firms with moderate levels of relatedness. These findings have implications for theory, research, and practice. We discuss these below.

Implications for theory and research

Recent research has highlighted the role of acquisitions as a mechanism for the redeployment of resources that are subject to market failure (Anand and Singh, 1997; Capron, Dussauge, and Mitchell, 1998). In this study we investigated the effectiveness of such redeployment in the case of one set of resources that are very susceptible to market failure, knowledge-based or technological resources. Our results provide both good and bad news.

[2] Specifically, for the *i*th firm and *t*th period, knowledge stock (K_{it}) was computed using the formula $K_{it} = 1 - \delta(K_{it-1}) + R_{it}$, where δ stands for depreciation rate for knowledge capital, and R_{it} represents the current-period knowledge flow addition. The initial stock of capital was computed by dividing the first observed year's flow by $\delta + g$, where g is the firm's historic rate of growth of real expenditures on R&D (Henderson and Cockburn, 1996).

The positive outcome of this evaluation is that, *when the characteristics of acquisitions are accounted for*, acquisitions improve the technological performance of the acquiring firm. Although prior research concluded that acquisitions reduce innovative outputs, this study suggests that under the appropriate circumstances, even after controlling for innovative inputs such as R&D, acquisitions can introduce a positive shock onto innovation output. This finding is also consistent with the sheer volume of acquisition activity in the high-technology sector that suggests that managers also view acquisitions as a mechanism for accessing technology.

The results of this study are also important from a broader economic perspective. The rapid growth of technical knowledge in the past few decades has meant that building and maintaining expertise in multiple technologies is difficult for even the largest corporations (Granstrand and Sjolander, 1990; Arora and Gambardella, 1994). Yet, bringing together different streams of knowledge is becoming an important precondition to successful innovation in many industries (Grant, 1996; Powell, Koput, and Smith-Doerr, 1996). This need for increased differentiation in the development of knowledge and increased integration in its application has given new importance to technology markets (Demsetz, 1991; Grant, 1996). Our results indicate that the process of obtaining technological assets from external sources and matching them with internally developed assets to enhance their productivity can work, at least insofar as the frequency of innovation output is concerned.

The above arguments highlighted the brighter aspects of the results. Another perspective on these results, however, draws attention to their less positive facets. Prior research has identified three kinds of deficiencies in the context of organizational learning: hubris, or underestimating the likelihood of failure or the difficulty of the task at hand; overexploration, or venturing into domains of completely new knowledge; and, overexploitation, or focusing only on the immediate neighborhood of the well known and understood and overlooking more distant options (Levinthal and March, 1993). Our data and results indicated evidence of all three kinds of errors. To the extent that relative size serves as a measure of the relative difficulty of integration, it appears that underestimating the magnitude of the integration task is not uncommon. Further, the variation on relatedness, and the curvilinear relationship that we identified between acquisition relatedness and innovation output, suggests that in selecting acquisitions managers err in both directions, acquiring both businesses that are only distantly related or unrelated to the existing business, as well as those that are too closely related to the current business. The problems of acquiring unrelated businesses are well documented and our results further reinforce those lessons (Singh and Montgomery, 1987). Additionally, our findings help to highlight errors in the opposite direction. Managers do make mistakes in picking acquisitions that are too closely related to their extant domains, and these mistakes are penalized with poorer performance. Thus, we find some empirical evidence of 'competency traps' (Levinthal and March, 1993).

Implications for measurement

Our findings also have implications for the literature on acquisitions in general. Managerial hubris and agency problems (Roll, 1986; Hayward and Hambrick, 1997), imitation effects (Haunschild, 1993), inappropriate application of learning (Haleblian and Finkelstein, 1999), and underestimating the process impediments to postacquisition integration (Jemison and Sitkin, 1986; Hitt *et al.*, 1996; Singh and Zollo, 1997) are all valid and complementary explanations for why acquisitions consistently fail to help the acquiring firm. The findings of this paper suggest an additional explanation, one that is perhaps more sympathetic to managerial motivations and decisions. Evaluating all acquisitions on the same performance metric, for instance financial performance, may not be appropriate. Acquisitions motivated by different objectives may differ in their timing and mode of impact on firm performance.

The recent literature has provided several exciting ways of using patent data to measure the construct of knowledge (Mowery, Oxley, and Silverman, 1998; Jaffe *et al.*, 1993; Stuart and Podolny, 1996). We build on these studies by presenting an additional set of measures and applying them to the context of acquisitions. The patent-based approach to knowledge measurement used by this study, and similar approaches used in prior studies (e.g., Stuart and Podolny, 1996), have several strengths. A primary strength of such approaches is that by using information on individual elements of knowledge these approaches make possible a fine-grained assessment of a firm's knowledge base. Research has argued that a firm's knowledge base should ideally be reflected as an asset on its balance sheet (Granstrand and Sjolander, 1990). Although that remains unattainable at present, these kinds of measures do provide some basis for quantifying this asset and enabling further analysis. A second strength of these approaches is that they enable continuous, and highly informative and detailed, measurement of difficult constructs such as technological relatedness. Finally, another virtue of these approaches is that they permit quantification of knowledge bases from publicly available data, in a longitudinal context.

The use of distributed lags to study the dynamics of postacquisition performance represents another potential contribution of this study. Although the distributed lag technique has been used by economists, relatively few researchers in the strategy area have used this methodology. This approach could be extremely useful in a variety of strategic contexts that entail studying the impact of an event or strategy on the performance of a unit across several periods.

Implications for managers

The findings of this study draw managers' attention to several paradoxical aspects of the acquisition selection and integration process. This study indicates that larger absolute size and smaller relative size of acquisitions are associated with superior postacquisition performance for the acquiring firm. Further, a moderate level of relatedness is preferable to acquiring a firm that is very closely related, or distant to the acquiring firm. Thus, from the acquisition selection standpoint this research suggests that a balance on both size and relatedness of acquisitions is favored.

Limitations and future research

Several limitations of this study are worth noting. The restriction of the sample to a single industrial context reinforces the need for conducting the study in other industries. Additionally, the relevance and utility of the patent-based measures of knowledge are likely to be limited to industries in which patents are themselves meaningful indicators of innovation. In addition to the chemicals sector some of the other contexts in which these measures could be applied include biotechnology, semiconductors, industrial machinery, and advanced materials.

Another limitation of this study that suggests an area of future research is the use of patents to measure innovative output. Although patents are reasonably good indicators of innovative output, they are best regarded as intermediate outcomes between acquisitions and value creation. While our results indicate that acquisitions accelerate the creation of technologically new combinations and innovations, they do not allow us to directly measure the value generated by these innovations. Examining the economic value of postacquisition innovations would be a natural extension of the work in this study and would enable a more complete assessment of the contribution of technological acquisitions to technological development.

Finally, in this paper we used only a simple count measure for nontechnological acquisitions. However, such acquisitions could themselves vary on many dimensions and reflect many different objectives. The development of a schema to measure the various dimensions of nontechnological acquisitions and relating them to different types of firm outcomes would be another fruitful direction of further research.

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APPENDIX

The list of patents obtained by a firm, and the patents cited by the firm in the patents obtained by it, is used as the measure of the firm's knowledge base. Since a firm's own patents represent knowledge created by the firm, their use as components of the firm's knowledge base is natural. However, the use of patents *cited* by the firm as a component of the firm's own knowledge base may require further explanation.

Patent citations represent an acknowledgement of the contributions of prior work in the development of the current invention. As Jaffe *et al.* (1993: 580) note:

> The granting of the patent is a legal statement that the idea embodied in the patent represents a novel or useful contribution over and above the previous state of knowledge, as represented by the citations. Thus, in principle, a citation of Patent X by Patent Y means that X represents a piece of previously existing knowledge upon which Y builds.

A citation thus represents a restriction on an owner's rights to exploit her own patent, and is therefore not likely to be made if the cited patent does not truly represent knowledge underlying the current patent.

The legal aspects of the patenting process also ensure that patents that *do* truly represent preexisting knowledge are cited with accuracy in patents that build upon them. First, all applicants are required by law to acknowledge all 'prior art' through citations. Second, to oversee this process, each patent and its citations must be cleared by a patent examiner before the patent is actually granted. The patent examiner, who is usually an expert in the technological domain under which the patent falls, conducts a search of the prior art in the area and adds any citations that the patent applicant's own search may have missed. Since citations circumscribe the exploitable domain of the applicant's patent, the patent applicant is likely to contest these citations if they do not accurately represent prior related knowledge. Together, this system represents a set of checks and balances that ensures that patent citations are relatively robust indicators of knowledge flows (Trajtenberg, 1990; Jaffe *et al.*, 1993). Thus, the assignee of a patent is likely to know the contents of the patents cited by her, at least to a level of familiarity, and perhaps to mastery.