Do High Technology Acquirers Become More Innovative?

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Abstract

This paper draws on organisational, managerial and financial theories to analyse acquirer characteristic effects on innovation performance. For 2624 high technology US acquisitions over a three year post-acquisition window, the sample as a whole records early reverses followed by positive changes in R&D-intensity and insignificant changes in R&D productivity. Within the average effect, and controlling for acquisition endogeneity and for commonly identified deal-specific effects, significant acquirer characteristic effects emerge. A large but "general" acquirer knowledge base enhances the R&D productivity consistent with improved capacity to select and absorb targets. High acquirer leverage levels raise R&D productivity gains consistent with enhanced monitoring induced efficiency. However, rapid leverage changes reduce R&D-intensity consistent with increased financial constraints and short-termism.

Keywords: Acquisitions, Innovation, Propensity score

1. Introduction

There has been an impressive record of global acquisition activity involving high technology firms, i.e. R&D-intensive firms whose investments are characterized by long time horizons (Chandler, 1994). In the 1990s alone, the value of high technology acquisition activity surpassed $1.93 trillion spread across 8058 deals worldwide. This paper explores the extent to which managers' apparent enthusiasm for acquisitions is justified by examining whether the high technology acquirers improve their post-acquisition innovation performance. We focus on two performance aspects: innovation inputs proxied by R&D spend relative to assets which we refer to as R&D-intensity and innovation productivity proxied by successful patent applications relative to R&D spend which we refer to as R&D productivity.

There are theoretical arguments for expecting a beneficial acquisition effect on both aspects of innovation performance. For example, within the resource-based approach of the firm, acquisitions can be regarded as an important strategic weapon through which a firm can enhance its asset base, while avoiding the time-consuming internal accumulation of innovation enhancing resources (Dierickx and Cool, 1989; Barney, 1991; Teece et al., 1997). Equally, acquisitions can be employed as a means of renewing and revitalizing the existing knowledge base of a firm and of avoiding the inertia and simplicity that result from its repeated exploitation (Capron and Mitchell, 1998; Vermeulen and Barkema, 2001). According to traditional economic approaches, acquirers, by becoming larger, can benefit from R&D related economies of scale. Thus, a larger firm may benefit by overcoming indivisibilities in R&D projects (Calderini and Garrone, 2003; Cassiman et al., 2005), or because it has a larger and more stable internal stream of resources to finance R&D (Himmelberg and Petersen, 1994). A larger firm can improve its R&D productivity by the spreading of the fixed R&D costs over larger production output, better capacity utilization, and increased specialization of management and scientists (Cassiman et al., 2005). Finally, it may be argued that a larger firm can benefit from economies of scope by exploiting opportunities for cost savings and risk-sharing when it carries out numerous R&D projects under the same roof (Baumol et al., 1982; Henderson and Cockburn, 1996).

However, the evidence on the impact of acquisitions on the acquirers' innovation performance does not accord with these positive predictions. Studies looking at the acquisition effect on proxies for the inputs to the R&D process report a neutral effect (Danzon et al., 2007; Hall, 1988, 1999; Healy et al., 1992) or a significantly negative effect (Hall, 1990a; Hitt et al., 1991, 1996; Ravenscraft and Scherer, 1987). Similarly, studies looking at the acquisition effect on proxies for the acquirers' R&D output report a neutral effect (Prabhu et al., 2005) or a significantly negative effect (Hitt et al., 1991).[1]

Scholars studying the relationship between acquisition activity and innovation performance have attempted to reconcile theory and evidence by developing a number of process-based arguments. A negative effect of acquisition on innovation performance has been attributed to the diversion of managerial time and energy from the R&D process (Hitt et al., 1991, 1996); to disruptions to the R&D process and organizational routines (Haspeslagh and Jemison, 1991; Ranft and Lord, 2002; Puranam et al., 2006), to a low retention rate of the acquired firms' key employees, or to a lack of effective motives for the acquired firm's inventors (Calderini et al., 2003; Chaudhuri and Tabrizi, 1999; Ernst and Vitt, 2000; Ranft and Lord, 2000); to organizational, business and technological dissimilarities between the acquiring and acquired firms (Chakrabarti et al., 1994; Hagedoorn and Duysters, 2002; Ahuja and Katila, 2001; Cassiman et al., 2005; Prabhu et al., 2005; Cloodt et al., 2006) or the pursuit of rationalisation of R&D in the face of excess capacity or poor returns (Danzon et al., 2007).

In this paper, we advance the debate on the relationship between acquisition activity and innovation performance in three ways. First, we offer an analysis of the acquisition effect on innovation performance by studying both the impact of acquisition on R&D-intensity (measured by the ratio of R&D expenditure to total assets) and on R&D productivity (measured by the ratio of successful patent applications per $million of R&D expenditure) of the acquirers. Most

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[1] These results are consistent with studies which suggest that acquisitions have neutral or negative effects on financial or share price performance for acquiring firms (King et al., 2004; Cosh and Hughes, 2009; Cosh, Guest and Hughes, 2005, 2008).

previous studies focus on only one of these dimensions. Studying the impact on both dimensions allows us to distinguish input from output effects in the same sample of acquisitions and to examine the extent to which performance is affected to the same way by the acquisition event.

Second, we seek to explain the variance of the acquisition outcomes on innovation inputs and outputs by focusing on the characteristics of the acquirer. This is consistent with recent work (Sorescu et al., 2007), which emphasizes the importance of the characteristics of the acquirer as a key determinant of acquisition outcomes, over and above the deal-specific characteristics of the acquirer and acquired taken as a pair in terms, for example, of their market relatedness or technical similarities (e.g. Ahuja and Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006). Our approach is based on the view that whatever the deal-specific characteristics or motivation of an acquisition may be, its exploitation will be affected by the ability of the acquirer to identify and exploit those opportunities. In developing our approach to relevant acquirers' characteristics we draw from organizational learning (Cohen and Levinthal, 1989; Makadok, 2001; Zahra and George, 2002) and managerial and financial economics (Jensen and Meckling, 1974; Jensen, 1986; Laverty, 1996; Marginson and McAulay, 2008). We use these approaches to develop arguments, in particular, about the factors that are likely to enhance the acquirers' absorptive and financial capacity to select appropriate acquisition targets and benefit from acquisitions. We thus develop and test hypotheses about the moderating impact on innovation performance of the size and concentration of the acquirer's knowledge base across different technology fields and of the leverage level and growth that an acquirer experiences at the time of acquisition. We include for completeness variables to control for a number of deal-specific characteristics

Finally, a novel methodological feature of our analysis is that it accounts for the possible endogeneity of the decision to carry out an acquisition to certain acquirer characteristics. To do this our analysis adopts the propensity score approach (Rosenbaum and Rubin, 1983, 1984), which addresses the problem of potential acquisition endogeneity to observable firm characteristics in the creation of the acquirers' counterfactual innovation performance (i.e. the performance consequent on the non-occurrence of an acquisition). The empirical analysis is conducted using a sample of 2624 acquisitions that were conducted by publicly traded high technology US acquirers. To the best of our knowledge, this is the largest sample of high technology US acquisitions in the literature.

The remainder of this paper is organized as follows. The next section develops the theoretical background and hypotheses of the paper. It is followed by a section describing the dataset and the methodology employed. Then, the empirical results from the analysis are presented. The final section highlights the key findings of the analysis and draws out their implications.

2. Theoretical background and hypotheses

2.1. The acquisition effect on innovation performance

We are concerned with the question of whether and how acquisitions affect innovation performance in terms of inputs and productivity and the factors affecting those changes.

The extant acquisition/innovation literature offers a number of insights. Hitt et al. (1991) contemporaneously study the acquisition effect on R&D-intensity (R&D/sales) and patent intensity (patents/sales), using a sample of 191 US manufacturing acquisitions from 1970 to 1986, and find a significantly negative effect on both metrics. A negative effect on both R&D-intensity and the new products/sales ratio is also found by Hitt et al. (1996), who use information collected from questionnaires from a sample of 250 manufacturing US firms for the period 1985-1991. Cassiman et al. (2005), using interviews with managers in 31 international technology-based horizontal acquisitions, condition post-deal R&D inputs (R&D personnel, lab equipment), output (technological knowledge, patents, new processes/products) and performance (returns to R&D expenditures) on the technological and market relatedness of the merging firms. However, their study, focuses on relatedness, and does not offer evidence on the overall acquisition effect on innovation performance. A number of other studies have enhanced our understanding of the relationship between acquisition and innovation performance but they have focused their analysis on proxies for R&D inputs alone (Ravenscraft and Scherer, 1987; Hall, 1988, 1990a, 1999; Miller, 1990; Healy et al., 1992; Danzon et al., 2007) or on R&D output alone (Chakrabarti et al., 1994; Ernst and Vitt, 2000; Ahuja and Katila, 2001; Hagendoorn and Duysters, 2002; Calderini et al., 2003; Cloodt et al., 2006). We investigate both in a framework which conditions the possible outcomes in terms of the pre-acquisition characteristics of the acquirer whilst including controls to capture some key deal-specific characteristics which have featured in previous work (e.g. Ahuja and Katila, 2001; Cassiman et al., 2005).

Our emphasis on the acquirers' side is based, first, on the argument that post-acquisition decisions – including those about innovation – tend to be housed primarily within the acquirer's departments (Zollo and Singh, 2004), and that the managers from the acquirer tend to "colonize" the target by providing it with their own management tools (Hambrick and Canella, 1993). Secondly, in high technology environments, in particular, where knowledge depreciates rapidly (Glazer and Weiss, 1993), the capability of the acquirer to exploit the acquired knowledge base is a key determinant of the post-acquisition innovation performance. We draw on theories from the organizational learning literature and managerial and financial economics to develop arguments about the factors that are likely to enhance this capability. Our focus, in particular, is on the acquirers' absorptive and financial capacity to select appropriate acquisition targets and exploit the acquired knowledge base after the deal.

2.2. The acquirer's absorptive capacity

According to Cohen and Levinthal (1989, 1990), a firm's ability to recognize the value of new, external information, assimilate it, and apply it to commercial ends depends on its absorptive capacity. The concept of absorptive capacity in an acquisition context implies that firms with superior absorptive capacity should be better positioned to carry out and benefit from acquisitions for two main reasons. On the one hand, they are more capable relative to rivals of scanning the corporate market and selecting the "appropriate" acquisition targets with reference to their strategic objectives. This aspect of absorptive capacity is related to what has been called resource-picking (Makadok, 2001) or potential absorptive capacity (Zahra and George, 2002) in the management literature. These terms are used to capture the capability in selecting target resources and describe the mechanism that makes firms receptive to assimilating externally generated knowledge. Such firms tend to have the routines that allow them to analyse, process and understand external information before acting. Interpreting these concepts in a corporate acquisition context, superior absorptive capacity results in benefits for potential acquirers either from encouraging acquisitions of the appropriate targets or from discouraging them from carrying out inappropriate acquisitions.

However, identifying and acquiring majority control of a firm is not enough; the assumed benefits materialize only when the acquirer exploits the acquired firms' resources during the acquisition implementation stage (Haspeslagh and Jemison, 1991; Ranft and Lord, 2002). This aspect of absorptive capacity is related to the concepts of capability building (Makadok, 2001) or realized absorptive capacity (Zahra and George, 2002), which have been employed to capture the capability of firms to deploy, transform and exploit the acquired resources. As Cohen and Levinthal (1989, 1990) put it, firms with a higher absorptive capacity will have developed transferable learning skills across different bodies of knowledge. Interpreting these concepts in a corporate acquisition context, acquirers with a superior absorptive capacity are relatively more capable of deploying the acquired resources and fully exploiting the innovation potential of the acquired knowledge base. On the basis that a firm's accumulated knowledge base through R&D activity enhances the potential and realised absorptive capacity of a company, we propose the following hypothesis:

Hypothesis 1. Acquirers with a large knowledge base will experience a higher R&D productivity, as a result of an acquisition, relative to acquirers with a small knowledge base.

The second critical dimension of an acquirer's knowledge base is the way that knowledge is distributed across different technology fields. Understanding the way in which the composition of an acquirer's knowledge base impacts acquisition outcomes is limited. Our attention, here, is focused on the degree of concentration of an acquirer's knowledge base, which is measured using standard concentration indices (see section 3.3.2 for details). The concentration notion has the advantage, over similar proxies used elsewhere, that it accounts for both the number of classes that a firm's patents fall and the number of patents per patent class.[2] Our discussion about the relationship between the knowledge base concentration of the acquirer and R&D productivity of an acquisition has different implications for acquisitions in related and unrelated product markets.

In related acquisitions, we expect a positive relationship to hold between the degree of an acquirer's knowledge base concentration and its post-acquisition R&D productivity. In line with the absorptive capacity theory, the greater the knowledge base concentration of a firm, the greater its expertise in specific technology fields, and the greater its competence is identifying appropriate acquisition candidates and assimilating and exploiting the acquired knowledge. Along similar lines, Prabhu et al. (2005), using a sample of 149 pharmaceutical acquisitions from 1988 to 1997, find that the acquirer's R&D output (new drugs in clinical trials) is positively related to its depth of knowledge. However, it can be argued that, even in the case of related acquisitions, a concentrated specialised knowledge base may limit some exploitation potential. For example, the potential for synergies through resource redeployment across different knowledge areas may be diminished, along with the potential for "pleasant accidents" in the R&D process (Cohen and Levinthal, 1989; Prabhu et al., 2005). On balance, however, we expect that a large and concentrated knowledge base will enhance an acquirer's absorptive capacity in the case of related acquisitions. Hence, we predict a positive relationship between the interaction of the size of an acquirer's knowledge base and the concentration of the

[2] Prabhu et al. (2005) account for these dimensions separately, by defining knowledge "breadth", as the number of classes that acquiring firm's patents fall in each year, and knowledge "depth", as the number of the acquiring firm's patents per technology patent class in each year.

knowledge base across technology fields and the acquisition effect on R&D productivity. Our second hypothesis is thus:

Hypothesis 2. In related acquisitions, the interaction between the size and concentration of an acquirer's knowledge base will be positively associated with the acquirer's R&D productivity, as a result of the acquisition.

In unrelated acquisitions, although a larger knowledge base will still enhance the acquirers' absorptive capacity, we expect a negative relationship to hold between the degree of an acquirer's knowledge base concentration and its post-acquisition R&D productivity. In other words, we argue that "generalist" acquirers will be better positioned relative to "specialists" acquirers to benefit from unrelated acquisitions. This is because, as the degree of knowledge concentration increases, the acquirer's knowledge profile becomes excessively field-specific and narrow in scope. As a result, the acquirer is likely to have a rather poor understanding of the new knowledge embedded in unrelated targets. In the target selection stage, "specialist" acquirers are likely to have an impaired peripheral vision (Day and Schoemaker, 2006), hindering effective target selection. In the acquisition implementation stage, "specialist" acquirers might suffer from core rigidities (Leonard-Barton, 1992), leading to a lack of understanding of the routines in and idiosyncrasies of the acquired firm. These arguments highlight the need to maintain some degree of knowledge base diversity in order to successfully import and exploit external knowledge in unrelated acquisitions. We therefore state our third hypothesis:

Hypothesis 3. In unrelated acquisitions, the interaction between the size and concentration of an acquirer's knowledge base will be negatively associated with the acquirer's R&D productivity, as a result of the acquisition.

2.3. The acquirer's financial capacity and the intensity and productivity of R&D

A key determinant of successful target integration and effective exploitation of the acquired knowledge base is the degree to which the acquirer has the required financial capacity to sustain investments in complementary assets, including R&D and related human and physical capital investments and reorganisation (Teece, 1986, 2006; Hughes and Scott Morton, 2007). In so far as high levels of debt limit the ability to raise finance to do this or reduce internal free cash flow then an important obstacle to such investments will be the acquirer's financial leverage (Hall, 1990a, 1994; Hoskisson and Hitt, 1994: 65-66; Hitt et al., 1996).

These arguments lead to the prediction that there will be a negative impact on the resources devoted to the R&D process by both the level and growth of leverage at the time of acquisition, but it is useful to disentangle the possible reasoning behind each separately. Researchers have offered several explanations for the trade-offs imposed by a high level of leverage. On financial grounds, high debt levels will imply that a significant amount of cash flow has to be devoted to servicing the debt and hence fewer funds will be available for R&D (Hall, 1990a, 1994; Miller, 1990). Another explanation is based on the phenomenon of economic short-termism that is often blamed on biases against long-run investments (Laverty, 1996; Marginson and McAulay, 2008). Given that a high level of leverage implies a relatively high financial risk to the company, managers of highly leveraged acquirers will be likely to try to avoid risky investments with long-horizon payback periods, like R&D. Increased levels of debt are also likely to limit managers' discretion, either because debt holders have imposed strict covenants for the provision of their funds (Smith and Warner, 1979), or because risk-averse debt holders' importance in the firm has increased and they dislike investments creating non-redeployable assets, as R&D investments often do (Hitt et al., 1996). High leverage *per se*, however, may not have an adverse effect if it represents for the firm concerned an optimal capital structure given its investment opportunities and its choice amongst the "pecking order" of sources of finance. It is a well known result in financial theory that, faced with value enhancing investment opportunities, managers will use internal cash flow first, then debt and only finally, when leverage is maximised, issue new equity (Myers and Maljuf, 1984). High leverage *per se* may therefore not be a constraint. In relation to leverage growth, significant leverage rises at the time of a new corporate acquisition may put the acquirers' resource pool and their resource allocation mechanisms under significant strain by using up available leverage possibilities. Evidence consistent with this argument is that significant increases in leverage (an increase in long-term debt greater than 75 percent of a firm's market vale) are followed by declines in R&D-intensity (Hall 1990a, 1994). Taking these arguments together, we express the following overall leverage hypothesis:

Hypothesis 4. Acquirers with (a) a high level of leverage or (b) a high growth of leverage at the time of acquisition will experience a lower R&D-intensity, as a result of the acquisition, relative to acquirers with a low leverage level or growth.

Arguments for expecting an impact of the level of leverage on R&D productivity have not been systematically addressed in the literature. The arguments here relate not only to cash flow issues but also to questions of extracting value from investments. The latter raises questions of governance and the monitoring of managers' behaviour. In this case positive effects may be predicted. Thus, debt may be viewed as a disciplinary mechanism that ensures that managers act in the shareholder's interests (Jensen and Meckling, 1974; Jensen, 1986). This is because managers in highly leveraged firms must expose their strategic decisions to the scrutiny of the capital markets to administrate the exploitation of value from assets. This can be expected to lead to pressures for efficient selection of targets and the more efficient deployment of resources among competing R&D projects in the post-acquisition period. This suggests a positive link between the level of leverage and post-acquisition R&D productivity. The relationship between leverage growth and R&D productivity is more complex. Debt financed acquisitions require full new disclosure of financial and strategic information in capital markets (Hoskisson and Hitt, 1994: 110). This involves the danger that there will be leakages of key strategic information about the acquirer to competitors, or of information about the target firm to other potential bidders, which might lead to a bidding war. Given the higher financial and strategic costs involved in externally funded acquisitions, we predict that such acquisitions are likely to involve an expectation for higher synergies – including R&D productivity improvements – in order to make the net acquisition payoff positive. However, a high growth of leverage over a short period in time, which will be the case in debt-financed acquisitions, can result in a radical shift in the managers' investment preferences towards pursuing smaller, lower risk and lower return R&D projects with relatively short payback periods to satisfy investors (Laverty, 1996; Marginson and McAulay, 2008). Although this type of investment choices may prove to be detrimental to the long-term R&D productivity of a firm, the resultant strategy may have positive results on the short-to-medium term R&D productivity. In the context of the immediate post-acquisition effect we expect both influences to lead to positive impacts on R&D productivity in the post-acquisition period. Hence, we hypothesize:

Hypothesis 5. Acquirers with (a) a high level of leverage and (b) a high growth of leverage at the time of acquisition will experience a higher R&D productivity, as a result of the acquisition, relative to acquirers with a low leverage level or growth.

3. Methods

3.1. Sample

We construct a large, unbalanced panel of US publicly traded firms during the period from 1984 to 1998. The panel includes high technology firms, that is, firms with their primary activity in SIC 28 Chemicals and Allied Products, SIC 35 Industrial and Commercial Machinery and Computer Equipment, SIC 36 Electronics and Electrical Equipment, SIC 37 Transportation Equipment, SIC 38 Measuring, Analyzing and Controlling Instruments; Photographic, Medical and Optical Goods, and SIC 48 Communications (see Hall and Vopel, 1996). The database contains information on firms' acquisition activity collected from Thomson Financial's SDC

Platinum, R&D and financial data from Standard and Poor's Compustat database, and patenting activity from the NBER dataset which includes all the utility patents granted by the US Patent and Trade Office (Hall et al., 2001).

To construct our sample, we first identified the population of firms engaging in acquisition activity through the SDC Platinum database. The database contains a comprehensive coverage of US acquisitions since the beginning of the 1980s. We searched the population of all publicly traded acquirers that are incorporated in the US. There are 1672 such firms that carried out at least one acquisition during the period 1984-1998. We collected data on their acquisitions, which are defined as deals where the acquirer owns less than 50% of the target's voting shares before the takeover and it increases its ownership to at least 50% as a result of the takeover. Table 1 shows the year distribution of 6618 acquisitions and the 4179 acquirers during the period 1984-1998.[3] Next, we added to our sample 2177 publicly traded US firms, which were drawn from the population of firms listed in the Standard & Poor's Compustat database and which operated in the same industries as those in our SDC Platinum dataset (thus yielding a total sample of 3849 firms). To complete our dataset, we augmented it with R&D, financial and patenting data for all the firms included in our sample. The Compustat database was used to provide annual firm-level R&D and financial data. Patenting data on successful applications were derived from the NBER version of the US Patent and Trade Office database. Because firms often register patents under their subsidiaries' names, we used Dun & Bradstreet's "Who Owns Whom" annual issues to obtain their detailed corporate structure of our sample firms and the data was aggregated to the parent firm level.

Combining data from the different databases and imposing data requirements that arise from the empirical analysis – especially patenting activity, where only 1821 of the 3849 firms are linked to a patent assignee – the effect of acquisitions on innovation performance is estimated using a panel of 1423 US public high technology firms and 8949 firm-year

[3] An individual firm will appear as an acquirer in our dataset whenever it increases its ownership of a target's voting shares from less than 50% to at least 50% as a result of the takeover. If a given firm carries out more than one acquisition in the same year, it will appear only once in our list of acquirers for that year.

observations during the period 1984-1998. Of these 1423 firms, 573 firms carry out at least one acquisition during the sample period and 850 firms carry out no acquisition. Although there are some differences between the 1423 sample firms and the full set of 3849 firms that were initially considered, the magnitude of the differences does not raise representativeness issues.[4] The resulting sample includes a total of 2624 acquisitions. These deals involve 1621 acquirers, of which, 1064 make a single acquisition in a given year and 557 carry out multiple acquisitions in a given year. Table 1 shows the year distribution of the 2624 acquisitions and of the 1621 acquirers involved in these acquisitions. The table also discriminates between acquirers making multiple acquisitions within a year and acquirers making a single acquisition within a year. The 2624 acquisitions involve 1223 (47%) privately held targets, 1077 (41%) former subsidiary units that have been divested by their former parent, 291 (11%) publicly traded targets, and 33 (1%) units that are reported by SDC either as former joint ventures or their public status is unknown.

[Insert Table 1 about here]

3.2. Model specification: the causal acquisition effect on innovation performance

The central problem that arises in examining the acquisition effect on an acquirer's innovation is to estimate the changes relative to the 'counterfactual position' of what would have happened had an acquisition not occurred. Researchers have tried to estimate the counterfactual performance by utilizing information from non-acquiring firms, against which the observed performance of the acquiring firms can be judged. However, if that performance differs systematically between acquiring and non-acquiring firms (which will be the case if engagement in acquisitions is endogenous to firm characteristics shared by the two groups of firms), then the performance of non-acquiring firms will be a biased estimate of the counterfactual performance

[4] The mean firm size (ln total assets) for the 1423 sample firms is 11.6 compared with 10.4 for the remaining firms in the initial sample with some data available over the sample period ($p<0.01$). The two groups of firms differ slightly with respect to innovation performance: the mean R&D-intensity is 0.11 for the sample firms and 0.14 for the remaining firms in the initial sample ($p<0.01$), while the mean R&D productivity is 0.7 for the sample firms and 0.53 for the remaining firms in the initial sample ($p<0.01$).

of the acquiring firms. To overcome this problem, we employ the propensity score approach, which controls for selection-on-observables (Rosenbaum and Rubin, 1983, 1984). Assuming that possible differences between acquiring and non-acquiring firms can be captured by a vector of pre-acquisition firm characteristics, we define and control for the predicted probability that a given firm will make an acquisition conditional on its pre-acquisition characteristics. This predicted probability is the so-called "propensity score". Our analysis employs the propensity score weighting approach that has been suggested by Hirano et al. (2003). They show that weighting by the inverse of an estimate of the propensity score leads to an efficient estimate of the average 'treatment' effect, which in our terms is the acquisition effect on innovation performance.

The estimation of the acquisition effect follows closely an algorithm similar to that adopted by Danzon et al. (2007). At the first stage, the propensity score (*p*) is estimated on the basis of lagged values of acquirer economic and financial characteristics (see section 3.4 for details). At a second stage, we estimate the acquisition effect for each of the three post-acquisition years, t+1, t+2, t+3, and for the three year average, which should be less sensitive to the effect of year-to-year fluctuations. We perform weighted least squares (WLS) by regressing the percentage change in R&D-intensity and R&D productivity on a dummy variable that equals one if the firm makes an acquisition in year t and on industry and year dummies. The weights for firm-year observations in which an acquisition takes place are equal to $1/p$ and the weights for the observations without an acquisition are equal to $1/(1-p)$. In this way, acquiring and non-acquiring firms that are likely to have had comparable innovation performance in the absence of an acquisition receive higher weights. The coefficient of the acquisition indicator measures the average acquisition effect on innovation performance. Our approach deals directly with the bias due to observable characteristics. Finally, we measure our dependent variables in terms of changes, thus allowing for time-invariant unobservable differences among firms and, hence, we also account for unobserved heterogeneity (Todd, 1999; Bryson et al., 2002; Danzon et al., 2007). [5]

3.3. Measures

3.3.1. Dependent variables

Innovation performance is measured using data on R&D expenditure and successful patent applications. Although we acknowledge that both R&D expenditure and patents are subject to numerous limitations as innovation indicators (see Kleinknecht et al., 2002), combining R&D and patent data allows the creation of composite constructs that do relatively well in capturing the innovation performance of high technology firms (Griliches, 1990; Hagedoorn and Cloodt, 2003; Narin et al., 1987). Patents are considered by application date, but only patents which are actually granted are counted. The application date is preferred to the grant date, because the actual time of inventions is closer to the application date than to the subsequent grant date, which depends upon the review process of the patent office (Hall et al., 2001). Our analysis of the acquisition effect on innovation performance centres on two variables, R&D-intensity and R&D productivity.

Percentage change in R&D-intensity. R&D-intensity is measured by the ratio of R&D expenditure to total assets. Normalizing R&D expenditure by a proxy for firm size ensures that our measure is not affected by changes in the size of the acquirers that take place after acquisitions of new assets or after divestments of unwanted parts following acquisitions. The percentage change of R&D-intensity is calculated from t-1 to t+1, t+2 and t+3 respectively, as well as from t-1 to the average R&D-intensity over the period from t+1 to t+3. Focusing on the three post-acquisition years is similar to practice that has been employed in earlier work on

[5] These variant unobservable effects may still be present. However, we should note first that controlling for observables bias may be considered more important than controlling for bias due to unobservables (Heckman et al., 1998). Moreover, although instrumental variables and Heckman selection estimators can deal with selection-on-unobservables, as Bryson et al. (2002) argue, the identification of suitable instruments is often a practical obstacle to successful implementation of these estimators. Inappropriate instrument selection can be a serious problem because the resulting estimates are contingent on the underlying distributional assumption relating to the unobserved variables.

acquisitions and innovation but also on the accounting profitability of acquisitions.[6] A three-year window has the advantage that achieves a balance between the time required for possible acquisition effects to materialize and the estimation difficulties arising from the presence of additional confounding factors in longer estimation windows and reduces sample observation losses due to data unavailability and an inability to analyse acquisitions occurring towards the end of the sample period.

Percentage change in R&D productivity. R&D productivity is measured by the ratio of the number of successful patent applications over R&D expenditure in $million (1996 prices). This ratio is frequently referred to in the literature as "propensity to patent". Statements about R&D productivity effects are subject to time lags intervening between R&D investments and patent applications. It, however, should be noted that where acquisitions are made of companies with impending patent applications based on their past innovative investments then such effects could in principle appear rapidly in the acquirer's records. The percentage change of R&D productivity is calculated from t-1 to t+1, t+2 and t+3 respectively, as well as from t-1 to the average R&D productivity over the period from t+1 to t+3. The averaged value has the advantage that it is less sensitive to the time lag intervening for the transformation of R&D inputs to R&D output compared with the patent/R&D ratios for each individual year.

3.3.2. Independent variables

Acquisition. This is an indicator that equals one in years in which a firm makes at least one acquisition and equals zero otherwise. We consider all the completed acquisitions during the period 1984-1998.

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[6] Our review of the literature on the acquisition-innovation relationship shows that scholars studying the acquisition effect on the intensity of R&D employ a minimum of a 1-year window (Hall, 1988) and a maximum of a 3-year window (Hall, 1990a, 1999; Hitt et al., 1991, 1998; Healy et al.,1992; Danzon et al., 2007). Scholars studying the acquisition effect on patenting activity employ a minimum of a 2-year window (Calderini et al., 2003 - they refer to this window as the medium-term effect), others use a 3-year window (Hitt et al., 1991; Ernst and Vitt, 2000), while others use a maximum of a 4-year window (Ahuja and Katila, 2000; Cloodt et al., 2006; Calderini et al., 2003 - they refer to this window as the long-term effect). For a review of studies on the accounting profitability of acquisitions that use a 3-year window see King et al., (2004) and Cosh and Hughes (2009).

Knowledge base size. The size of the acquirer's knowledge base is proxied by the patent stock (e.g. see Dushnitsky et al., 2005).[7] The stock is calculated using the standard perpetual inventory formula. According to the perpetual inventory equation, the patent stock at time t, PS_t, equals the last period's patent stock, after depreciation at rate δ is deducted, plus the number of patents at time t, P_t: $PS_t = (1-\delta)PS_{t-1} + P_t$. Following Hall (1990b) and others, we assume a 15% depreciation rate per annum. For the purpose of the regression analysis, the patent stock is transformed using its square root in order to reduce the large variability arising from count data.

Knowledge base size x Knowledge base concentration. The acquirer's knowledge base concentration is measured using the distribution of its patents during the 5 pre-acquisition years across the technology fields defined by the 3-digit patent classification.[8] Concentration is calculated using the Hirschman-Herfindahl index and takes values from zero to one. Letting P_j be the number of patents in class *j*, *P* be the total number of patents a firm holds, n be the number of classes in which patents fall. Then,

$$\text{Knowledge base concentration} = \sum_{j=1}^{n} \left(\frac{P_j}{P} \right)^2$$

The size of the knowledge base is measured as described above. This interaction of the two variables is identified separately for related and unrelated acquisitions in accordance with hypotheses 2 and 3 (the variable for related acquisitions is discussed below).

Leverage. Leverage is measured by the ratio of long-term debt to the book value of common equity. *Leverage growth.* The acquirer's leverage growth over the acquisition period is measured as the change between the last pre-acquisition year and the first post-acquisition year. Although it may be due to other reasons this leverage growth is highly likely to be caused by the debt-financing of acquisitions.

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[7] We proxy the knowledge base using the stock of patents rather than of R&D expenditure, because the patent series does not suffer from the time discontinuities present in the R&D expenditure series.
[8] The five-year-period (starting six years before the acquisition year) is similar to the periods that have been employed for the construction of knowledge-based variables elsewhere (e.g. Ahuja and Katila, 2001; Sorescu et al., 2007).

3.3.3. Control variables

The analysis controls for industry- and time-specific differences in firm characteristics and economic conditions by using industry and year dummy variables.[9] Three other control variables are employed to test the robustness of our findings to the inclusion of three key deal-specific characteristics that have been used in earlier work.

Related acquisitions. This dummy variable is employed to discriminate between acquisitions of targets operating in similar versus different product markets. It might be the case that R&D synergies are harder when two firms operate in different industries (Hitt et al., 1991; Chakrabarti et al., 1994; Hagendoorn and Duysters, 2000; Ahuja and Katila, 2001). It is measured by a dummy variable that equals one for acquisitions where the acquiring and the acquired firms have their primary industrial activity in the same 3-digit SIC code. We have considered only horizontal and not vertical acquisitions in the related class of deals, following considerations that there exist dissimilarities in technologies, markets and operations of firms operating in upstream versus downstream industries. This dummy variable equals one for related and zero for unrelated acquisitions.

Public target acquisitions. This dummy variable is employed to discriminate between acquisitions of public targets versus acquisitions of private firms and former subsidiary units. The former tend to be larger and acquisitions of public targets are likely to be qualitatively different from those involving non-public targets (Desyllas and Hughes, 2008). It is measured by a dummy variable that equals one for acquisitions of publicly traded target firms.

Cross-border acquisitions. This variable is employed to discriminate between domestic and cross-border acquisitions. In cross-border acquisitions, apart from the usual challenges in post-acquisition integration that apply to domestic acquisitions, there is the dimension of geographical distance and national differences. The R&D-intensity might suffer due to the

[9] The industry dummies are defined at the 2-digit SIC level, except for biopharmaceutical firms active in SIC 283 that are considered separately from chemical firms active in SIC 28 (excluding 283). We discriminate between biopharmaceutical and chemical firms because the former tend to be considerably more R&D-intensive firms compared with the latter.

imposition of strict financial rules (Hitt et al., 1996), while R&D productivity might suffer due to different national cultures making knowledge transfers harder (Maskell and Malmberg, 1999). Cross border acquisition is measured by a dummy variable that equals one for acquisitions where the acquiring and acquired firms are incorporated in different countries.

Sample means and standard deviations of the focal variables for all the sample acquirers and non-acquirers are reported in Table 2.

[Insert Table 2 about here]

3.4. The estimation of propensity score

The probability of making an acquisition (i.e. the propensity score) is estimated using a logit regression. The dependent variable takes on two values, 0 and 1, depending on whether a firm makes an acquisition in year t. The independent variables employed include proxies for pre-acquisition firm characteristics (firm size, growth, profitability, leverage, R&D-intensity, R&D productivity, and knowledge base size) measured in t-1 and industry and year dummies. Appendix A provides definitions, descriptive statistics and correlations for all the variables. The estimated coefficients from the logit regression analysis are presented in Appendix B. The results suggest that acquirers are indeed not a random sample of firms, but that they have distinctive characteristics. In particular, they are significantly larger firms and they have a significantly lower pre-acquisition R&D-intensity compared with non-acquirers. Therefore to be the extent that these factors affect post-acquisition outcomes and pre-acquisition target selection strategies then a method that assumes that acquisitions are exogenously determined with respect to these will produce a biased estimate of their causal effects.

Although the propensity score is higher on average for the acquiring firms than for the non-acquiring firms (0.34 vs. 0.17), there is a substantial overlap in their distribution. A potential source of bias might arise from "mismatching" acquiring and non-acquiring firms, which happens when for some acquiring firms there are no comparable non-acquiring firms

(Heckman et al., 1997).[10] To account for this, we impose the "common support" condition. We eliminate observations on acquiring firms whose propensity score is larger than the largest score of non-acquiring firms; and observations on non-acquiring firms whose propensity score is smaller than the smallest score of acquiring firms. As a result, 24 observations fall out of our sample - including 20 acquisitions – leading to a sample of 8949 observations and 2624 acquisitions. A common characteristic of the four acquirers in the 20 acquisitions that fall out is the relatively large firm size (ln total assets is in excess of 16.5). These firms are General Electric Co, Eastman Kodak Co, Intel Corp and Raytheon Co. For the 8949 observations in our sample, we check whether conditioning on propensity score balances the covariates between the acquiring and non-acquiring groups of firms, i.e. the two groups of firms should be on average observationally similar. For this purpose, each covariate is regressed on a dummy variable discriminating between acquiring and non-acquiring firms, the estimated propensity score and industry and year dummies. We find that the acquisition dummies are statistically insignificant in the regressions of all the covariates of the logit regression. Therefore, controlling for propensity score does reasonably well in balancing the covariates between the acquiring and non-acquiring firms.

4. Results

4.1. The acquisition effect on R&D-intensity and R&D productivity

Table 3 reports the results from WLS regressions for estimating the causal acquisition effect on R&D-intensity. Panel A reports results for the full sample, which includes observations where an acquirer carries out both single and multiple acquisitions in a given year. Panel B reports results for a reduced sample that includes single deals only. The results from the analysis using the reduced sample have the advantage that they are insulated from a possible aggregation bias. They also allow us to check the robustness of our findings to the inclusion in the set of

[10] In fact, being able to identify a number of observations where there is no overlap between acquiring and non-acquiring firms raises questions about the robustness of traditional regression methods relying on functional form to extrapolate outside the common support (Bryson et al. 2002).

regressors of proxies for deal-specific characteristics. We regress the percentage change of R&D-intensity from t-1 to t+1, t+2 and t+3, respectively, on an acquisition dummy and industry and year dummy variables. In the last two columns, we estimate a similar regression but now the dependent variable is the percentage change of R&D-intensity from t-1 to the average R&D-intensity over the period from t+1 to t+3. The coefficient of the acquisition dummy is the impact of an acquisition after controlling for the acquisition propensity through performing WLS. In each period, we also estimate an augmented specification with the characteristics of the acquirers that were hypothesized to moderate the acquisition effect on innovation performance. For this purpose, each characteristic is interacted with the acquisition dummy.

Looking at the specification including only the acquisition dummy and taking the three post-acquisition years as a whole in column 7, we find a positive but statistically insignificant acquisition effect on R&D-intensity of 5.2% in Panel A and 13% in Panel B. If we look at individual year effects, we see that this is the result of a fall and recovery over the years from t+1 to t+3. Thus, in column 1 we see that the acquirers experience a significantly lower R&D-intensity in the first post-acquisition year relative to non-acquirers (-24.8%, p<0.01 in Panel A; -20.4%; p<0.01 in Panel B). However, there is a tendency for R&D-intensity to rebound since t+2, leading to a statistically and economically significantly positive effect on R&D-intensity in t+3 (76.9%, p<0.10 in Panel A; 91.2%, p<0.05 in Panel B).[11] It should be noted that, had we ignored the endogeneity of acquisitions, Ordinary Least Squares regression estimates would incorrectly suggest that acquisitions have a negative - yet statistically insignificant - effect on R&D-intensity over the three post-acquisition years (e.g. -10.3%, p=0.24 for the full sample). The significantly negative effect on R&D-intensity in the first post-acquisition year is consistent with previous studies emphasising the influence of temporary restructuring costs and the disruption of established organizational and R&D routines in early post acquisition years (Haspeslagh and Jemison, 1991; Ranft and Lord, 2002).

[11] This positive trend in R&D-intensity relates to a changing sample of firms since the number of observations falls by about 28% between t+1 and t+3. However, similar results emerged when we re-estimated the regressions in t+1 and t+2 over the same 6421 observations present in t+3 of Panel A (results not shown). Thus, when we did this we obtained a coefficient for the acquisition dummy equal to -32% in t+1 (p<0.01), 7% in t+2 (p=0.64) and 17.3% over the period from t+1 to t+3 (p=0.35).

[Insert Table 3 about here]

Panels A and B of Table 4 report the results from similar WLS regressions for the acquisition effect on R&D productivity. Taking the three post-acquisition years as a whole in column 7 of Panel A, we find an insignificantly negative acquisition effect on R&D productivity of -4.7%. The negative acquisition effect on R&D productivity appears to be more pronounced in the reduced single-deal sample of Panel B when we find a significantly negative acquisition effect on R&D productivity of -8% ($p<0.10$). Again, had we ignored the endogeneity of acquisitions, we would have incorrectly estimated a positive - yet statistically insignificant - acquisition effect on R&D productivity over the three post-acquisition years (e.g. 1.1%, p=0.69 for the full sample). The time profile is similar to the effects of acquisition on R&D-intensity. Thus, in columns 1 and 3 of Panel B we obtain significantly negative effects of -12.9% ($p<0.05$) in t+1 and -11.5% ($p<0.05$) in t+2, but in column 5 an insignificantly positive effect of 9.9% in t+3.[12] These results are once again consistent with restructuring, exploitation and implementation time lags in the post-acquisition period.

[Insert Table 4 about here]

4.2. The absorptive and financial capacity of the acquirers

These neutral to positive medium-term acquisition effects on R&D-intensity and negative to neutral medium-term acquisition effects on R&D productivity are, however, aggregated outcomes across acquirers differing in pre-acquisition characteristics. We now, therefore, explore whether some acquirers are capable of doing better than average. We focus on the augmented specifications in columns 2, 4, 6 and 8 of Tables 3 and 4 where the regressions include the moderating characteristics of the acquirers. In addition in Panel B of these tables these columns include deal specific control variables relating to relatedness, whether the target

[12] Re-estimating the regressions over the 6421 observations present in t+3 (results not shown) we obtained similar results: the coefficient for the acquisition dummy equals -4.9% in t+1 (p=0.50), 0.3% in t+2 (p=0.97) and 1.9% during the period from t+1 to t+3 (p=0.35).

is a public firm and whether the acquisition was cross-border. We focus our discussion on average 3-year effects.

In Table 4 we find strong support for Hypothesis 1 which predicts that the acquirers with a large knowledge base will experience a relatively higher post-acquisition R&D productivity. Thus, the results in column 8 of Table 4 show that for every unit increase in an acquirer's knowledge base, there is a 0.7% increase in all deals in R&D productivity and a 1.6% increase in single deals ($p<0.01$ in both cases). If we focus on column 8 of Panel B for the effects of moderating variables, we find that, in related acquisitions, the interaction between the size and concentration of an acquirer's knowledge base is negatively (-2.7%; $p<0.10$) associated with the acquirer's R&D productivity. This is a rejection of Hypothesis 2, which predicted a positive link. However, we find support for Hypothesis 3, which predicts that, in unrelated acquisitions, the interaction between the size and concentration of an acquirer's knowledge base will be negatively associated with its post-acquisition R&D productivity. A unit increase in the interaction term leads to a 6.1% decrease in the R&D productivity of that acquirer ($p<0.01$). Therefore in both unrelated and related acquisitions, the results indicate the existence of a negative relationship between the interaction of the size and concentration of an acquirer's knowledge base and its post-acquisition R&D productivity. The effect is, however, much stronger in unrelated acquisitions. In the case of related deals the negative effect may reflect an inability to recognise or benefit from 'pleasant accidents' and resource redeployment. The coefficient of Knowledge Base Size x Concentration in Panel A shows a significantly positive impact over the three year period as a whole but which is falling over time. That coefficient is, however, estimated without the fuller set of regressors included in Panel B. [13]

We now turn to the evidence on the impact of an acquirer's financial capacity. We find no support for Hypothesis 4a, which predicts a negative relationship between an acquirer's level

[13] The regression using the full sample in Panel A, does not allow us to discriminate between related and unrelated acquisitions because many acquirers acquire both related and unrelated targets in the same year. The reason behind the contradictory evidence from Panels A and B is some aggregation bias arising from the presence of multiple deals. Re-estimating the same regression specification of Panel A including single deals only, we obtained a consistently and significantly negative coefficient for Knowledge Base Size x Concentration, which equals -2.6% in t+1 ($p<0.10$), -5.2% in t+2 ($p<0.01$), -8.7% in t+3 ($p<0.01$), and -4.7% for the average from t+1 to t+3 ($p<0.01$).

of leverage and its post-acquisition R&D-intensity. In Table 3, we obtain an insignificantly negative coefficient for the 3-year post-acquisition period in column 8 in both panels ($p<0.01$). Looking at the individual years, we obtain a significantly positive coefficient for leverage in t+1 in both panels ($p<0.01$). One possible explanation for this is that if firms which rely heavily on acquisition programs also tend to be relatively highly leveraged (Hitt et al., 1996), then the variable may be acting as a proxy for acquisition experience. Thus, acquirers with a track record of acquisition and an accumulated leverage might be better positioned to overcome possible disruptions of R&D and organizational routines associated with the acquisition process. Alternatively, to the extent that high leverage is associated with enhanced monitoring and control effects, managers may be incentivised to invest in assets needed to extract gains from R&D programmes earlier than in lightly monitored situations. This is also consistent with the time profile of the coefficients in both panels of Table 4 which shows strongest effects in the earlier years.

In contrast, we find support for Hypothesis 4b, when we turn to leverage growth and the results on R&D-intensity in Table 3. We find evidence for a consistently negative relationship between an acquirer's leverage growth at the time of acquisition and its post-acquisition R&D-intensity. The coefficient of leverage growth is significantly negative in the regressions for all the different periods in both panels. The results from the regressions in Column 8 for the % change of R&D-intensity from t-1 to the average R&D-intensity over the period from t+1 to t+3 suggest that a unit increase in leverage growth at the time of acquisition leads to a 6.5-11.5% decrease in R&D-intensity ($p<0.01$ in both panels).

The implication of leverage and leverage growth for R&D productivity are explored in Table 4. As far as the relationship between leverage and post-acquisition R&D productivity is concerned, it appears that a high level of leverage before the time of acquisition is beneficial for the post-acquisition R&D productivity, which is in accordance with Hypothesis 5a. For both samples, a statistically significantly positive coefficient is obtained in the first two post-acquisition years and over the 3-year period. The results from the regressions in Column 8 suggest that a unit higher level of leverage before the time of acquisition leads to a 3-3.5% rise in post-acquisition R&D productivity (p<0.01 in both panels). These results are consistent with our earlier finding that R&D-intensity is also enhanced for leveraged acquirers immediately after acquisition. This would be expected to increase the likelihood of extracting value from an acquisition's innovative potential. Some support is also found for Hypothesis 5b, according to which there is a positive relationship between an acquirer's leverage growth and R&D productivity. The relationship is stronger in Panel A regressions compared to Panel B, where the coefficient is statistically significant only in t+2 and over the 3-year period. The results from column 8 of Panels A and B suggest that a unit increase in an acquirer's leverage growth at the time of acquisition leads to a 1.5-6.6% rise in its R&D productivity (p<0.01 in both panels). However, as argued earlier, this positive relationship might actually have a negative connotation reflecting short-termism. Taken together, we find statistically significant and quantitatively important positive leverage effects on post-acquisition R&D productivity, while high growth rates of leverage associated with the acquisition year lead to significant falls in R&D-intensity, but without prejudice to medium-term R&D productivity.

If we now turn to the control variables, other important effects of disaggregation across types of deal emerge. Here we focus on Panel B of Tables 3 and 4. Table 3 Column 8 shows that the impact on R&D-intensity appears to be significantly worse in acquisitions of public targets and in cross-border acquisitions, while no conclusion can be drawn with respect to the market relatedness of the two firms. The higher integration costs involved in both cross-border deals and acquisition of public targets are likely to impose a significant strain on the acquirers' managerial and financial resources at the expense of the R&D process. They arise from substantial transaction and integration costs in the case of typically larger public deals and from high implementation, acculturation and regulatory costs in the case of cross-border deals. In Table 4, we find that post-acquisition R&D productivity is significantly lower after related acquisitions and in acquisitions of public targets. The result that related acquisitions lead to lower R&D productivity is consistent with the interview evidence of Cassiman et al. (2005), according to which there might be a larger potential for acquirers to learn from unrelated acquisitions. The evidence that acquisitions of public targets harm both the inputs devoted to the R&D process and R&D productivity is consistent with the evidence that large scale public deals are relatively more associated with restructuring and capacity rationalisation than smaller private deals and with evidence that high technology acquirers making acquisitions of private companies gain from targeting opportunities to fill gaps in their exploitation pipeline (Danzon et al., 2007; Desyllas and Hughes, 2008). Finally, it is important to note that in the case of single deals our results taken together suggest that, despite the fact that deal-specific characteristics have a sizable effect on post-acquisition innovation, acquirer characteristics play an important role in explaining the variance of acquisition outcomes.[14]

5. Discussion and conclusion

In this paper we address the question whether and under what conditions high technology acquirers improve their innovation performance. We examined the acquisition effect on innovation performance in terms of both R&D-intensity and R&D productivity. Furthermore, we explored whether some acquirers possess a superior absorptive and financial capacity that make them relatively more successful in carrying out acquisitions.

Taking our samples in aggregate over the three post-acquisition years, we found neutral to positive effects of acquisition on R&D-intensity and negative to neutral effects of acquisition

[14] The results above refer to the acquiring firms, and examine whether an acquisition leads to improved innovation performance relative to non-acquirers (a similar approach is adopted by Danzon et al. 2007). An alternative approach would be to create an artificial pre-acquisition 'combined' firm of the acquirer and the target and compare the performance of this 'combined' firm before and after acquisitions. There are several data problems in attempting to do this for the very large number of private acquisitions which occur. There are, however, other reasons for believing that our results based on acquiring firms alone would be robust to this approach if it was feasible. First, Desyllas and Hughes (2009), compare the characteristics for the couples of acquiring and acquired in 212 high technology acquisition between public US firms during the period 1984-1998 for which such data is available. This shows that the acquired firms tend to be significantly more R&D-intensive (R&D/assets) compared with their acquirers, while they have a somewhat lower but statistically insignificant different patent-intensity (patents/assets) from their acquirers. This means that our results of a decline in R&D-intensity in t+1 are not the result of a composition effect, which would tend to raise post-acquisition intensity. Second, although "combined" effects might be present in year t and perhaps in t+1, these effects on the acquirers' innovation performance will tend to dissipate as time elapses after the acquisition year. Thus, Calderini et al. (2003), who investigate the effect of acquisitions on the innovation performance of the acquired firms, argue that *"[a] two-year period was a reasonable estimation of the interval potentially needed to abandon or restructure any applied-research programme*" (Calderini et al., 2003: 130). Therefore, the regressions where the dependent variables are the % change in the acquirers' R&D-intensity and R&D productivity from t-1 to t+3 are unlikely to be affected.

on R&D productivity. We also found important differences within these average findings both in terms of the time profile of effects and across different types of acquirers.

The results from the analysis suggest that acquisitions bring about a negative effect on both R&D-intensity and R&D productivity in particular in the first year following an acquisition. This finding is likely to reflect the influence of temporary restructuring costs and the disruption of established organizational and R&D routines (Haspeslagh and Jemison, 1991; Ranft and Lord, 2002). As far as the R&D-intensity is concerned, we find that by the third year the effect is positive. In relation to the acquisition effect on R&D productivity, we find that the magnitude of the negative effect diminishes with time, with an overall neutral effect. Our aggregate results based on a very large sample of firms are less negative than previous evidence (e.g. Hitt et al., 1991). One potential reason for this is that our propensity score adjusted estimation of the causal acquisition effect on innovation performance eliminates a downward bias potentially present in previous estimates. In particular, the results from the first-stage of our analysis suggest that acquirers have a significantly lower R&D-intensity compared with non-acquirers. Had we ignored this acquirer feature, we would have obtained a downward biased estimate of the causal acquisition effect on R&D-intensity such as characterise some previous studies.

Our analysis of the moderating factors in the average aggregate relationship between acquisition activity and innovation performance, focused on the role played by an acquirer's absorptive and financial capacity to carry out acquisitions. An acquirer's absorptive capacity during the processes of target selection and resource deployment is proxied by the size and concentration of its technological knowledge base. Its financial capacity to sustain a certain level of investments in order to benefit from an acquisition is proxied by the level and growth of its leverage at the time of acquisition.

The results from the analysis show that some acquirers are indeed better positioned to carry out acquisitions due to a superior absorptive capacity (Cohen and Levinthal, 1989; Makadok, 2001; Zahra and George, 2002). We find that possessing a large knowledge base is associated with a relatively more positive acquisition effect on R&D productivity. We argue that this finding reflects the superior capacity of such acquirers to select appropriate targets and exploit the acquired knowledge base. Despite the finding that a large knowledge base increases an acquirer's R&D productivity, the results indicate that "generalist" acquirers (i.e. those with a non-concentrated knowledge base) do significantly better relative to "specialist" acquirers. Importantly, our analysis shows that a highly concentrated knowledge base is an unproductive R&D strategy, not only when acquirers buy targets that operate in unrelated markets, but also in related acquisitions, although as might be expected the negative effect is lower in the latter case.

For unrelated acquisitions, we interpret the negative estimated relationship as reflecting the fact that a highly concentrated knowledge base can be too field-specific, blocking the peripheral vision of the acquirer (Day and Schoemaker, 2006), which is essential for the selection of a suitable target, and leading to core rigidities (Leonard-Barton, 1992), which can hinder the post-acquisition resource redeployment process. For related acquisitions, the negative relationship between knowledge base concentration and R&D productivity may reflect two possible effects. First, as the degree of acquirer specialization increases, the potential for synergies through resource redeployment across different knowledge areas is diminished, as is the potential for "pleasant accidents" in the R&D process (Cohen and Levinthal, 1989; Prabhu et al., 2005). A second explanation of this finding can be developed within the context of the "exploitation-exploration" dichotomy (March, 1991; Levinthal and March, 1993). It has been suggested that firms can employ acquisition as a means of revitalising their knowledge base and avoiding the inertia and technological exhaustion that occur through the ongoing exploitation of a firm's existing knowledge base (Vermeulen and Barkema, 2001). On the basis of our findings, we argue that a firm's innovation strategy should not be simply thought of as consisting of the exploitation of the existing knowledge base through internal R&D, on the one hand, and the infusion of new knowledge through acquisitions or alliances, on the other hand. Firms should aim, instead, to maintain a good degree of knowledge base diversity through their own innovation activity in order to be able to select suitable acquisition targets and exploit the acquired knowledge base.

The results from the analysis also show that some acquirers are better positioned to benefit from acquisitions as a result of their pre-acquisition capital structure. Interestingly, it turns out that it is the growth of leverage that an acquirer experiences at the time of acquisition and not the level of leverage (as it has been implied by acquisition studies using subjective measures, e.g. Miller, 1990, Hitt et al., 1998), that matters for the acquisition effect on R&D-intensity. In accordance with studies on corporate restructuring, we find that acquirers with a high growth of leverage at the time of acquisition tend to suffer from significantly lower R&D-intensity compared with the rest of the acquirers (e.g. Hall, 1990a, 1994; Fox and Marcus, 1992). This leverage growth might be caused by the debt-financing of acquisitions, although leverage rises for other reasons will have a similar effect. We suspect that the significantly negative relationship between leverage growth and R&D-intensity reflects that – even if the large firms that make up the sample of acquirers reach a *modus operandi* with regard to a leveraged capital structure (Myers and Maljuf, 1984) – they are less able to afford the necessary post-acquisition R&D and capital investments when they are confronted with rapid leverage rises over a short period of time.

Once the analysis of the relationship between leverage and post-acquisition innovation performance is extended to the effects on R&D productivity, leverage looks more like a double-edged sword. Our results imply that acquirers with a high level of leverage enjoy a higher post-acquisition R&D productivity relative to the rest of the acquirers. This finding can be justified by the argument that a high debt level imposes discipline on management due to the scrutiny of strategic decisions by the capital markets (Jensen and Meckling, 1974; Jensen, 1986). Therefore, highly leveraged acquirers will be more likely to make prudent acquisition decisions compared with the rest of the acquirers. The results also provide some support for the existence of a positive relationship between leverage growth and R&D productivity. As was discussed, the positive effect of leverage growth on post-acquisition R&D productivity can have either a positive or a negative connotation. It will be positive to the extent that it reflects a higher potential for improving R&D efficiency which outweighs the relatively higher financial and strategic costs of debt financed acquisitions. However, the connotation will be negative if the positive estimated relationship actually reflects economic short-termism (Laverty, 1996; Marginson and McAulay, 2008). Given the finding that leverage growth is detrimental to R&D investments, it is possible to conjecture that there is a tendency for acquirers experiencing considerable leverage growth to – not only cut down R&D investments – but also shift the emphasis of investment towards smaller, lower risk R&D projects with relatively short payback periods. On this interpretation, a high leverage growth will lead to higher R&D productivity only in the short-to-medium term.

Our analysis of control variables reveals that there is an important distinction between acquisitions of large public targets and acquisitions of private targets and former subsidiaries. The latter are associated with a relatively higher post-acquisition R&D productivity. This is consistent with evidence on both the different scale of restructuring and integration costs associated with the acquisition of large public sector firms and a strategy of acquirers purchasing private targets to fill innovation pipelines (Dazon et al 2004, Desyllas and Hughes 2008).

Finally, we propose two extensions of this paper that emerge as promising directions for future research. The present work has shown that acquirer attributes help to explain the observed variance in acquisition outcomes, over and above the explanatory power of deal-specific characteristics (e.g. Ahuja and Katila, 2001; Cassiman et al., 2005; Cloodt et al., 2006). Future work should identify appropriate theories than will inform us on additional acquirer attributes upon which acquisition outcomes may depend on in order to augment the analysis of variance of acquisition outcomes accordingly. It will also be particularly interesting for future work to extend the line of analysis of this paper by focusing on the study of the interplay of acquirer- and deal-specific attributes. Such an approach will allow the systematic analysis of the way in which the profile of successful acquirers varies by acquisition type.

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Table 1
Year distribution of acquisition activity in sample, US acquirers 1984-1998

	SDC Platinum				Sample in analysis			
Year	No. of deals	No. of acquirers	No. of acquirers in single deals	No. of acquirers in multiple deals	No. of deals	No. of acquirers	No. of acquirers in single deals	No. of acquirers in multiple deals
1984	12	11	10	1	7	6	5	1
1985	121	90	68	22	58	42	30	12
1986	243	161	110	51	105	71	49	22
1987	192	143	104	39	94	64	42	22
1988	235	165	121	44	98	72	51	21
1989	306	222	165	57	161	116	88	28
1990	340	214	143	71	160	92	56	36
1991	350	242	175	67	156	111	83	28
1992	417	283	202	81	173	121	86	35
1993	487	326	227	99	189	125	83	42
1994	562	373	258	115	200	137	95	42
1995	677	422	282	140	247	149	93	56
1996	807	479	310	169	304	162	95	67
1997	863	493	312	181	329	174	102	72
1998	1006	555	347	208	343	179	106	73
Total	6618	4179	2834	1345	2624	1621	1064	557
Deals with value disclosed	4475				1684			
Total value (US$bn1996)	669.5				232.8			

The source of the data is SDC Platinum. The acquirers are US publicly traded firms with their primary activity in SIC 28, 35, 36, 37, 38, and 48.

Table 2
Descriptive statistics

Panel A: Sample acquirers

	Acquirers in all deals			Acquirers in single deals			Acquirers in multiple deals		
	No	Mean	S.D.	No	Mean	S.D.	No	Mean	S.D.
% Change in R&D-intensity									
From t-1 to t+1	1621	15.156	99.549	1064	17.852	106.733	557	10.006	83.987
From t-1 to t+2	1377	20.297	210.034	912	24.686	252.629	465	11.689	73.517
From t-1 to t+3	1153	33.740	570.247	767	43.212	695.037	386	14.918	106.508
Between t-1 and average from t+1 to t+3	1621	23.329	235.666	1064	28.500	283.503	557	13.452	89.486
% Change in R&D productivity									
From t-1 to t+1	1621	-8.707	143.294	1064	-3.640	167.347	557	-18.387	78.368
From t-1 to t+2	1377	-4.753	137.152	912	2.275	150.910	465	-18.538	103.841
From t-1 to t+3	1153	2.656	188.120	767	12.537	218.290	386	-16.978	102.492
Between t-1 and average from t+1 to t+3	1621	-12.412	120.938	1064	-5.117	137.075	557	-26.347	79.975
Independent Variables									
Knowledge Base Size $_{t-1}$	1621	11.303	12.540	1064	9.424	11.262	557	14.892	14.002
Knowledge Base Size x Concentration $_{t-1}$	1621	1.793	2.667	1064	1.699	2.826	557	1.972	2.326
Knowledge Base Size x Concentration $_{t-1}$ (Related)				369	1.835	3.304			
Knowledge Base Size x Concentration $_{t-1}$ (Unrelated)				695	1.627	2.535			
Leverage $_{t-1}$	1621	0.625	1.938	1064	0.535	1.992	557	0.797	1.820
Leverage Growth $_{\text{from } t-1 \text{ to } t+1}$	1621	0.657	1.658	1064	0.692	1.754	557	0.592	1.456
Control Variables									
Related Acquisition $_t$				1064	0.347	0.476			
Public Target $_t$				1064	0.133	0.339			
Cross-border Acquisition $_t$				1064	0.189	0.392			

Panel B: Sample non-acquirers

	No	Mean	S.D.
% Change in R&D-intensity			
From t-1 to t+1	7328	32.030	378.983
From t-1 to t+2	6204	39.644	510.912
From t-1 to t+3	5268	36.634	319.034
Between t-1 and average from t+1 to t+3	7328	37.371	333.240
% Change in R&D productivity			
From t-1 to t+1	7328	-5.694	112.853
From t-1 to t+2	6204	-4.017	132.500
From t-1 to t+3	5268	-1.950	139.951
Between t-1 and average from t+1 to t+3	7328	-9.113	101.894

Table 3

Weighted Least Squares regressions: analysis of acquisition effects on R&D-intensity (Dependent variable: % Change in R&D-intensity)

Panel A: All deals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Change between t-1 and:	t+1		t+2		t+3		Average from t+1 to t+3	
Constant	24.648***	28.564***	8.672	9.634	-60.680	-57.636	-15.660	-13.436
	(9.450)	(9.465)	(23.637)	(23.662)	(63.431)	(63.419)	(21.234)	(21.284)
Acquisition $_t$	-24.790***	-23.171***	-3.330	-0.300	76.854*	97.149***	5.216	10.735
	(6.462)	(6.476)	(14.917)	(14.978)	(40.495)	(40.721)	(14.521)	(14.562)
Interaction with Acquisition								
Leverage $_{t-1}$		2.585***		-1.988		-3.752		-1.675
		(0.828)		(1.921)		(5.744)		(1.861)
Leverage Growth $_{\text{from t-1 to t+1}}$		-3.043***		-2.972***		-24.021***		-6.520***
		(0.651)		(1.493)		(5.425)		(1.464)
No of Observations	8949	8949	7581	7581	6421	6421	8949	8949
No of Acquisitions	2624	2624	2176	0.2769	1790	1790	2624	2624
F-statistic	434.9***	399.9***	146.0***	133.0***	31.2***	29.3***	130.7***	120.4***
R-squared	0.51	0.51	0.28	0.28	0.08	0.09	0.24	0.24

*** p<0.01; ** p<0.05; * p<0.1.

Standard errors are in brackets. Industry and year dummies are included but not shown.

Panel B: Single deals only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Change between t-1 and:	t+1		t+2		t+3		Average from t+1 to t+3	
Constant	31.818***	25.587**	307.843***	321.649***	1019.321***	1069.993***	-17.703	-9.457
	(9.813	(10.015)	(26.853)	(27.061)	(71.994)	(72.870)	(22.557)	(23.006)
Acquisition $_t$	-20.392***	-29.334***	-0.793	13.731	91.152**	176.895***	13.026	30.956**
	(6.505	(6.856)	(15.332)	(16.156)	(41.776)	(44.527)	(14.952)	(15.749)
Interaction with Acquisition								
Leverage $_{t-1}$		2.385***		-2.814		-6.029		-2.002
		(0.894)		(2.109)		(6.479)		(2.053)
Leverage Growth $_{\text{from t-1 to t+1}}$		-2.279**		-11.543***		-32.001***		-11.525***
		(0.895)		(2.117)		(6.267)		(2.055)
Control Variables								
Related Acquisition $_t$		17.952***		3.935		-69.199**		-1.066
		(3.929)		(9.319)		(26.722)		(9.025)
Public Target $_t$		10.124		-47.829***		-165.173***		-51.550***
		(6.472)		(15.598)		(46.644)		(14.866)
Cross-border Acquisition $_t$		-1.599		-25.284		-114.660***		-34.379**
		(6.697)		(15.826)		(47.005)		(15.384)
No of Observations	8392	8392	7116	7116	6035	6035	8392	8392
No of Acquisitions	1064	1064	912	912	767	767	1064	1064
F-statistic	405.7***	330.3***	121.0***	99.0***	32.3***	27.5***	115.2***	95.3***
R-squared	0.50	0.51	0.25	0.26	0.09	0.10	0.22	0.23

*** p<0.01; ** p<0.05; * p<0.1.

Standard errors are in brackets. Industry and year dummies are included but not shown.

Table 4
Weighted Least Squares regressions: analysis of acquisition effects on R&D productivity (Dependent variable: % Change in R&D productivity)

Panel A: All deals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Change between t-1 and:	t+1		t+2		t+3		Average from t+1 to t+3	
Constant	-29.173***	-28.1301	26.877***	25.482	-18.607	-16.314	-40.633***	-40.567
	(8.255)	(8.140)	(8.613)	(8.303)	(11.345)	(11.369)	(6.366)	(6.246)
Acquisition $_t$	-8.975	-26.502***	-6.526	-28.254***	10.311	10.978	-4.733	-19.330***
	(5.645)	(5.658)	(5.436)	(5.330)	(7.243)	(7.499)	(4.353)	(4.341)
Interaction with Acquisition								
Knowledge Base Size $_{t-1}$		0.688***		0.953***		0.288		0.741***
		(0.256)		(0.228)		(0.301)		(0.197)
Knowledge Base Size x Concentration $_{t-1}$		9.314***		10.147***		-2.804***		6.691***
		(1.228)		(1.107)		(1.640)		(0.942)
Leverage $_{t-1}$		4.920***		4.639***		2.733***		3.459***
		(0.717)		(0.680)		(1.040)		(0.550)
Leverage Growth $_{\text{from t-1 to t+1}}$		6.940***		9.681***		0.254		6.595***
		(0.571)		(0.535)		(0.973)		(0.438)
No of Observations	8949	8949	7581	7581	6421	6421	8949	8949
No of Acquisitions	2624	2624	2176	2176	1790	1790	2624	2624
F-statistic	1219.9***	1075.7***	505.7***	481.9***	52.7***	44.1***	757.4***	683.3***
R-squared	0.74	0.75	0.57	0.60	0.14	0.14	0.64	0.66

*** p<0.01; ** p<0.05; * p<0.1.
Standard errors are in brackets. Industry and year dummies are included but not shown.

Panel B: Single deals only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Change between t-1 and:	t+1		t+2		t+3		Average from t+1 to t+3	
Constant	-25.907***	-10.748	14.658*	19.841**	-7.578	2.765	-37.135***	-25.788
	(8.263)	(8.411)	(8.497)	(8.509)	(12.453)	(12.591)	(6.161)	(6.262)
Acquisition $_t$	-12.845**	-7.454	-11.450**	-8.758*	9.946	28.959***	-7.965*	-1.943
	(5.478)	(5.906)	(4.852)	(5.203)	(7.226)	(7.981)	(4.084)	(4.397)
Interaction with Acquisition								
Knowledge Base Size $_{t-1}$		1.551***		2.189***		1.162***		1.643***
		(0.294)		(0.245)		(0.347)		(0.219)
Knowledge Base Size x Concentration (related) $_{t-1}$		-3.453*		-4.002**		-1.298		-2.704*
		(2.071)		(1.771)		(2.674)		(1.542)
Knowledge Base Size x Concentration (unrelated) $_{t-1}$		-0.929		-5.786***		-15.324***		-6.078***
		(1.921)		(1.626)		(2.495)		(1.430)
Leverage $_{t-1}$		4.310***		3.961***		1.717		3.002***
		(0.759)		(0.675)		(1.137)		(0.565)
Leverage Growth $_{\text{from t-1 to t+1}}$		0.931		1.743***		-1.339		1.498***
		(0.757)		(0.671)		(1.094)		(0.564)
Controls Variables								
Related Acquisition $_t$		-18.082***		-10.384***		-23.872***		-16.159***
		(4.024)		(3.523)		(5.603)		(2.996)
Public Target $_t$		-9.973*		-15.747***		-26.812***		-7.287*
		(5.447)		(4.920)		(8.104)		(4.055)
Cross-border Acquisition $_t$		-1.527		-3.127		-0.974		-2.967
		(5.636)		(4.993)		(8.153)		(4.195)
No of Observations	8392	8392	7116	7116	6035	6035	8392	8392
No of Acquisitions	1064	1064	912	912	767	767	1064	1064
F-statistic	1311.1***	964.3***	632.0***	465.0***	45.0***	34.4***	857.9***	634.9***
R-squared	0.77	0.77	0.64	0.65	0.12	0.13	0.68	0.69

*** p<0.01; ** p<0.05; * p<0.1.
Standard errors are in brackets. Industry and year dummies are included but not shown.

Appendix A

Table A1
Descriptive statistics

	Variable	Mean	S.D.	1	2	3	4	5	6	7	8
1	Acquisition	0.181	0.385								
2	Size	11.580	2.390	**0.33**							
3	Growth	0.316	1.281	**-0.03**	**-0.10**						
4	Profitability	0.011	0.432	**0.12**	**0.40**	-0.02					
5	Leverage	0.507	2.208	0.03	**0.08**	-0.02	**0.03**				
6	R&D-intensity	0.113	0.168	**-0.11**	**-0.34**	0.01	**-0.71**	**-0.06**			
7	Dummy Zero R&D	0.002	0.048	-0.02	**-0.04**	-0.01	**-0.08**	0.00	**-0.03**		
8	R&D productivity	0.694	1.599	**-0.04**	**-0.17**	**0.06**	-0.01	-0.02	**-0.07**	-0.02	
9	Knowledge Base Size	6.026	8.865	**0.29**	**0.72**	**-0.09**	**0.16**	0.05	**-0.12**	**-0.03**	**-0.01**

The number of observations is 8973. P<0.01 are bold.

Variable definitions

Acquisition is an indicator that equals one in years in which a firm makes at least one acquisition and equals zero otherwise. Size is proxied by the natural logarithm of total assets, which are measured in $1996 thousands. Growth is proxied by the annual growth of total assets. Profitability is proxied by operating return, which is calculated as the ratio of earnings before interest taxation, depreciation and amortization (EBITDA) to total assets. Leverage is measured by the ratio of long-term debt to the book value of common equity. R&D-intensity is measured by the ratio of R&D expenditure to total assets. Dummy Zero R&D is a dummy variable that equals one when R&D is equal to zero. R&D productivity is measured by the ratio of the number of patents over R&D expenditure in $1996 million. Knowledge Base size is proxied by the square root of the patent stock, which is measured using the standard perpetual inventory formula assuming a 15% depreciation rate per annum.

Appendix B

Table B1
Logit regression for estimating the propensity score of acquisition (Dependent variable: Acquisition $_t$)

Regressor	Coef.
Constant	-0.662***
	(0.051)
Size $_{t-1}$	0.043***
	(0.004)
Growth $_{t-1}$	0.000
	(0.003)
Profitability $_{t-1}$	0.055
	(0.038)
Leverage $_{t-1}$	0.000
	(0.002)
R&D-intensity $_{t-1}$	-0.137*
	(0.071)
Dummy Zero R&D $_{t-1}$	-0.108
	(0.098)
R&D Productivity $_{t-1}$	0.002
	(0.003)
Knowledge Base Size $_{t-1}$	0.001
	(0.001)
Number of Observations	8973
Number of Acquisitions	2644
Chi-squared	608.1***
Pseudo R-squared	0.1631
Log Likelihood	-3556.2

*** p<0.01; ** p<0.05; * p<0.1.

Estimated coefficients are reported in terms of marginal effects evaluated at the averages of the regressors. Standard errors are in brackets. Industry and year dummies are included but not shown.