Tangible slack versus intangible resources: the influence of technology slack and tacit knowledge on the capability of organisational learning to generate innovation and performance

Eduardo Bueno*
Facultad de CC.EE.
Universidad Autónoma de Madrid
Ctra. Colmenar Viejo, Km 15. 28049, Madrid, Spain
E-mail: eduardo.bueno@uam.es
*Corresponding author

J. Alberto Aragón
Facultad de CC.EE.
Universidad de Granada
Campus Cartuja s.n. Granada 18071, Spain
E-mail: jaragon@ugr.es

M. Paz Salmador
Facultad de CC.EE.
Universidad Autónoma de Madrid
Ctra. Colmenar Viejo, Km 15. 28049, Madrid, Spain
E-mail: maripaz.salmador@uam.es

Victor J. García
Facultad de CC.EE.
Universidad de Granada
Campus Cartuja s.n. Granada 18071, Spain
Fax: + 34 958 24 62 22
E-mail: victorj@ugr.es

Abstract: Literature has stated contradictory arguments about the importance of tangible and intangible resources. Meanwhile, the knowledge literature insists on the importance of tacit knowledge and a more traditional innovation literature and many practitioners have preferred to be focused on the importance of specific and tangible resources in organisational learning to generate innovative processes. In particular, the second perspective highlights the abundance of technological resources given the growing importance of information technology. Our sample of 575 technological firms operating in Spain shows that both resources are required to successfully implement the capability of organisational learning. Besides showing the positive relationship between this capability and the variables of innovation and performance, our
results find that tangible and intangible resources have positive relationships with innovation and performance. In any case, our analysis allows us to discover the particularly strong influence that the variables related to the intangible resource of tacit knowledge exert on the organisational learning, innovation and performance of the sampled firms in comparison with the more moderated impact of the tangible resources related to technological slack.

Keywords: resource-based view; technology; slack; tacit knowledge; organisational learning; innovation; performance.


Biographical notes:

Eduardo Bueno is a Professor of Strategic Management at the University Autonoma of Madrid, Spain, the Manager of the Knowledge Management Research Area of the Science Park of Madrid and the Manager of the Knowledge Society Research Centre.

J. Alberto Aragon-Correa is a Professor of Strategic Management at the University of Granada, Spain, and Rotterdam-Erasmus University, the Netherlands. He is the Head of the Department of Management at the University of Granada. His research work has been directed towards the study of environmental management, innovation and organisational learning.

M. Paz Salmador is a Professor of Strategic Management at the University Autonoma of Madrid, Spain, and a Senior Researcher at the Knowledge Society Research Centre of the Science Park of Madrid. She is also a Visiting Researcher at the Japan Advanced Institute of Science and Technology (Ishikawa, Japan) and at the National North-Western University (Resistencia, Argentina), as well as a Senior Fulbright Scholar at Texas A&M University (USA).

Victor J. Garcia-Morales is a Professor of Economics at the University of Granada, Spain. He is also an Investigator of organisational learning, knowledge management, innovation, flexibility and entrepreneurship.

1 Introduction

The resource-based view of the firm highlights the importance of the internal competencies of firms to obtain a successful performance of the organisations. In seminal contributions to this view (Barney, 1991; Wernerfelt, 1984), the firm’s resources or organisational capabilities to marshal these resources to produce superior performance determine competitive advantage. In the resource-based view, resources are classified as (Grant, 1991) tangible resources (such as equipment, capital, plants or stocks of raw materials) and intangible resources (such as reputation or knowledge). Besides, this perspective analyses organisational capabilities as the abilities to assemble, integrate and manage resources (such as organisational learning).
Previous applications of the resource-based view have concentrated on the importance of the capabilities to generate innovation or an improvement of financial performance. The capability of organisational learning has been shown as a positive and significant predictor of innovation (Calantone et al., 2002; Tushman and Nadler, 1986) and profitability (Schroeder et al., 2002; Bontis et al., 2002). However, it is not yet clear how resources influence the generation of those capabilities and, especially, which role (if any) is played by different kinds of tangible and intangible resources.

Literature has stated contradictory arguments about the importance of the different kinds of resources. The organisational learning literature insists on the positive relationship between the possession of tacit knowledge and the process of developing organisational learning (Nonaka and Takeuchi, 1995). However, the traditional innovation literature and many practitioners seem to prefer enough quantities of tangible resources in order to be able to generate innovative processes of organisational learning (Bourgeois, 1981). In particular, the importance of the abundance of technological resources is being highlighted by the second perspective because of radical evolutions in the areas of Information Technology (IT) and telecommunications.

Although there is an absence of both specific attention to the subject as well as clear findings in related literature, this debate has multiple and relevant implications. The importance of knowing more about the role of tangible slacks and the intangible capital of knowledge to examine the competitive potential of small firms and entrepreneurship is particularly clear. The traditional literature on innovation has led to an acceptance by scholars that small firms’ lack of resources often prevents them from implementing proactive strategies and that such initiatives are likely to reduce their profitability (Russo and Fouts, 1997; Rutherfoord et al., 2000). Hence, the vast range of investment devoted to Research and Development (R&D) by multinational firms such as IBM or Intel to maintain a differentiated advantage versus competitors that are more focused on the efficient usage of existent knowledge is often highlighted.

However, multiple new and successful organisations were born in the last decade with short resources. For instance, Microsoft, Apple, or other companies were born in garages just with the talent or vision of the founders. Therefore, it cannot be concluded from the available empirical evidence if the abundance of tangible or intangible resources are relevant conditions to generate innovative and profitable strategies in technological firms.

Additionally, in more general terms, organisational innovation is recognised nowadays as essential for firms trying to maintain or increase their competitive advantage (Ayers et al., 2001). These characteristics become even more evident in high-technology activities, which are reasons why this field turns out to be a particularly interesting context for the study of factors that have a bearing on new product development success (Langerak et al., 1997; Zirger and Hartley, 1996). New products and processes are important here because of the growing competition, globalisation, the increasingly faster evolution of technologies and the frequent changes in customer preferences (Cooper, 1993; Wind and Mahajan, 1997). Therefore, it is imperative that such assumptions about the different importances of tangible and intangible resources in generating innovation be based on empirical data, rather than on conjecture.

This article includes some reflections and hypotheses about the relationships of the tangible resource of technology slack and the intangible resource of tacit knowledge on the capability of organisational learning. We also analysed the relationship between
organisational learning and the variables of innovation and performance; that analysis also indirectly allows the possibility of examining the relationships between tangible and intangible resources with innovation and performance.

We used the data collected through a mail questionnaire survey of 575 technological firms operating in Spain to empirically explore our hypotheses. The findings, which are discussed in the final section, suggest that both kinds of resources are required to successfully implement the capability of organisational learning. Besides showing the positive relationship between this capability and the variables of innovation and performance, our results find that tangible and intangible resources have positive and significant relationships with innovation and performance. Even more appealing is that our simultaneous analysis of the variables allow us to highlight the particularly strong influence that the variables related to the intangible resource of tacit knowledge exert on organisational learning, innovation and performance in comparison with the impact of the variables associated with the tangible resource of technological slack.

This paper significantly contributes in at least three different ways. First, our finding supports the resource-based view argument about the importance of internal resources in the competitive advantage of firms. Second, the paper makes a significant contribution for a better understanding of the differentiated roles of tangible and intangible resources in the capability of organisational learning to generate innovation and performance. Third, our paper includes evidence from a wide sample of technological firms in a context differentiated from the traditional North American samples.

2 Theoretical background and hypotheses

2.1 The tangible resource of technological slack

We define ‘technological slack’ as the pool of technological resources in an organisation that is in excess of the minimum necessary to produce a given level of organisational output (we draw on the general delimitation for slack of Nohria and Gulati (1996) for our own definition). Technological slack may include an excess of working inputs, such as technologically-qualified employees or unused technological capacity.

Scholars have argued that organisational slack is an important catalyst for innovation for at least two reasons. First, slack is the “resource that enables an organisation both to adjust to gross shifts in the external environment with minimal trauma” (Bourgeois, 1981, p.31). A high discretion slack helps managers increase the perceived controllability of the external threats associated with searching for and adopting innovative processes, such as those of organisational learning.

Second, slack allows the pursuit of innovative projects because it protects organisations from the uncertain success of those projects, fosters a culture of experimentation (Bourgeois, 1981), introduces new products and enters new markets (Moses, 1992) or develops an emerging process of proactive environmental strategy (Sharma, 2000). Hence, slack facilitates some degree of ‘freedom’ to develop research or projects which do not usually generate any tangible outputs in the short term, but which may generate a knowledge basis for future high and unexpected success (see Mokyr, 1990, for a description of the discovery of post-it notes at 3M).
In any case, it is important to highlight that Sharfman et al. (1988) argued that only ‘high discretion slack’ in the form of free time and resources that can be applied to multiple situations and problems facilitates problem-solving behaviour. In contrast, ‘low discretion slack’ in such forms as idle machines and an excess of unqualified personnel usually has specific implications that may be unrelated to ease the generation of solutions. In our analysis we have delimitated technological slack considering its characteristics of ‘high discretion slack’, which can be defined as completely working inputs of the organisation.

Following such arguments, empirical studies on the organisational determinants of innovation have often shown a positive effect of technological slack (Majumdar and Venkatraman, 1993; Zajac et al., 1991). Thus:

**Hypothesis 1**

Technological slack will be positively associated with tacit knowledge in technological firms.

**Hypothesis 2**

Technological slack will be positively associated with organisational learning in technological firms.

### 2.2 The intangible resource of tacit knowledge

The right understanding of organisational learning demands distinguishing between the different dimensions and categories of knowledge (Bueno and Salmador, 2000; Nonaka, 1991; Scharmer, 2000; Spender, 1996). One of the most well-known distinctions is between explicit and tacit knowledge (Winter, 1987).

Explicit knowledge is well-structured and systematised, objective, rational and easy to capture, codify, express and share. Given the easiness of imitation by competitors and its lack of specificity (as it can be universally useful for different situations, objectives and contexts), explicit knowledge cannot be considered as a strategic asset of the firm.

On the other hand, tacit knowledge is very subjective and ambiguous, widely based on feelings and experiences more than on formal teaching and is not easy to structure or systematise. One of the best well-known characteristics of tacit knowledge is the difficulty in codifying it (e.g., writing a book). It is also easy to realise that tacit knowledge will be difficult to copy, imitate or share. It is highly strategic and dependent on the context and includes technical and cognitive dimensions. Tacit knowledge generates a better competitive advantage than explicit knowledge because of its difficulty in being imitated. Despite its strategic importance, the analysis of tacit knowledge has traditionally merited more theoretical than empirical attention (Hedlund and Zander, 1993), highlighting the importance of our analysis.

The process of organisational learning roots on the interaction between tacit and explicit knowledge. However, while explicit knowledge is usually present in a natural way in the firm’s context (e.g., corporate reports, accounting audits), tacit knowledge plays a more relevant role because of its ‘hidden’ presence in the organisation. Hence, although both kinds of knowledge (explicit and tacit) are positively related with organisational learning (Lam, 2000), it is usually accepted that tacit knowledge is the most interesting for the process of organisational learning because of its capacity to generate competitive advantage from its characteristic of difficult cost imitation (Nonaka and Takeuchi, 1995).
Different procedures emerge from tacit knowledge to reinforce the development of the capability of organisational learning (Nonaka and Takeuchi, 1995; Nonaka, 2004; Nonaka and Konno, 1998), for instance, through the process of socialisation (generating tacit knowledge from tacit knowledge) or the process of externalisation (generating explicit knowledge from tacit knowledge). Besides, the process of internalisation also contributes to the process of organisational learning that generates tacit knowledge from explicit knowledge. Meanwhile, combination is only related with explicit knowledge. Thus:

_Hypothesis 3_ Tacit knowledge will be positively associated with organisational learning in technological firms.

### 2.3 The implications for performance and innovation

Many works in the growing literature on organisational learning have noted a positive relationship between organisational learning and firm innovation (Calantone et al., 2002; Tushman and Nadler, 1986). Organisational learning supports creativity, inspires new knowledge and ideas and increases the ability to understand and apply them (Damanpour, 1991).

Generative learning, the most advanced form of organisational learning, occurs when an organisation is willing to question long-held assumptions about its mission, customers, capabilities or strategy and generate changes in its practices, strategies and values (Argyris and Schön, 1996; Senge, 1990). This kind of learning is a necessary underpinning for radical innovations in products, processes and technology (Senge et al., 1994).

A technological organisation committed to learning increases its innovative capability because the organisation is less likely to miss the opportunities created by emerging market demands. It has the ability and knowledge to anticipate and understand customer needs, possesses a greater state-of-the-art technology and uses that technology to innovate. It also has a stronger capacity to understand the strengths and weaknesses of its rivals and, thus, to learn from both their successes and their failures, enabling it to generate a greater innovation capability than its competitors (Calantone et al., 2002). Given these rationales and evidence, we advance the following hypothesis:

_Hypothesis 4_ Organisational learning will be positively associated with innovation in technological firms.

The literature emphasises the importance of organisational learning for a company’s survival and effective performance (Argyris and Schön, 1996; Senge et al., 1994). However, the empirical analysis of this relationship has been limited due to various difficulties such as ambiguity or the time delay between the two variables (today’s learning will affect tomorrow’s performance) and the possibility that the results of learning are disguised by exogenous factors. Organisational learning’s influence on the performance of technological firms should be analysed empirically, given that there is little knowledge available concerning the mechanisms by which organisational learning is transformed into performance (Snyder and Cummings, 1998; Inkpen and Crossan, 1995).
It is wrong to assert that an increase in organisational learning always leads to growth in organisational performance, since learning may not always improve an organisation’s results (Inkpen and Crossan, 1995). Nonetheless, generally speaking, organisational learning has a positive influence on performance improvements. This normally occurs not only in manufacturing firms, but also in technological companies (Argyris and Schön, 1996; Senge et al., 1994). Some recent works have begun to support this positive relationship in technological firms. Decarolis and Deeds (1999) and Stephan et al. (2000) maintained that knowledge generation, accumulation and application can be the source of superior performance and demonstrated the positive relationship between the knowledge flows and stocks and organisational performance in the biotechnology sector. Zahra et al. (2000) showed a strong relationship between international diversity and the mode of market entry and the breadth, depth and speed of a new venture firm’s technological learning, especially when the firm undertakes formal knowledge integration.

Thus, technological firms that show a greater breadth, depth and speed of organisational learning have higher performance levels (Hurley and Hult, 1998). The primary aim of organisational learning is to enhance performance quality and quantity, allowing the technological firm to increase and improve its sales, achieve more support and create, maintain and enlarge its customer base. Furthermore, technological organisations that learn and learn quickly gain a greater strategic capability that enables them to hold on to a position of competitive advantage and improve their results. These attitudes, behaviours and strategies of organisational learning will guide them to superior long-term performance.

Of course, we should not forget that technological organisations that encourage the learning spirit sacrifice, to some extent, immediate performance in order to achieve future performance, since immediate performance is due to the organisational learning drawn from yesterday while future performance will be the product of today’s learning process (Senge et al., 1994). Taking all of this into account, we propose:

**Hypothesis 5** Organisational learning will be positively associated with performance in technological firms.

Different theories have revealed that innovation is essential for better performance. Marketing theories reflect that the organisations that concentrate on the speed of innovation win a greater market share, which produces high income and high profitability. Strategy theories underscore that the organisations that adopt innovation first are able to create ‘isolation mechanisms’. Because the knowledge concerning innovation is not available to competitors, these mechanisms allow profit margins to be protected and important benefits to be gained. Finally, the theory of resources and capacities maintains that the set of human skills and their relations, the material resources, the reorientation of values, norms and culture and the knowledge a firm needs to develop different types of innovation, the organisation’s capacity to adjust to market demands through innovation and the availability of the capabilities and technologies needed to adopt the innovation make external imitation more difficult and allow firms to sustain their advantages more, meaning that the obtained benefits last longer.

The more valuable, imperfectly imitable and rare innovations (e.g., technological) are, the higher the performance will be. Technological organisations with greater innovation will achieve a better response from the environment, obtaining more easily the
Tangible slack versus intangible resources

... capabilities needed to increase organisational performance and consolidate a sustainable competitive advantage. Innovation not only stems from being conscious of a problem, but also from perceiving any opportunity to improve a certain aspect of organisational performance; in other words, innovation is brought into play in order to produce an improvement in organisational performance. Not promoting innovative projects and activities will have a negative effect on productivity and organisational performance (Hurley and Hult, 1998; Lööf and Heshmati, 2002; Zaltman et al., 1973). Thus, there is a positive link between innovation and organisational performance and between the different aspects of innovation (e.g., innovation design or speed, flexibility) and performance. The innovation literature also includes various empirical studies supporting this relationship, as well as different works that actually demonstrate it by using econometric methods (Calantone et al., 2002; Hurley and Hult, 1998; Lööf and Heshmati, 2002; Zaltman et al., 1973). Thus, we propose the following hypothesis:

Hypothesis 6 Innovation will be positively associated with performance in technological firms.

3 Methodology

This section presents the research methodology used in this study. We first describe the sample used, then discuss how each of the variables included in the study is operationalised and finally, present the statistical analysis.

3.1 Sample and procedures

The sample of firms was randomly selected from the Duns and Bradstreet 2001 database (Duns and Bradstreet Spain, 2000), which includes the 50,000 largest companies operating in Spain. The final sample contains 575 technological firms. Choosing a sample of technological firms located in a relatively homogeneous geographic, cultural, legal and political space enables the impact of the variables that cannot be controlled in the empirical research to be minimised (Adler, 1983). The Spanish market is relatively well developed and wholly integrated into the European Union (EU). It has had a slightly better rate of growth in recent years than the overall European market. However, Spain is in a geographical area that has received relatively little attention from organisational researchers.

Drawing on previous contacts, our knowledge about the key dimensions of this research and new interviews with five managers and six academics interested in the topic and who are familiar with the Spanish market, we developed a structured questionnaire to investigate how organisations face these strategic issues. These developmental interviewees did not provide data for the empirical investigation.

We decided to use CEOs as our key informants, since they receive information from a wide range of departments and are, therefore, a very valuable source for evaluating the organisations’ different variables (Baer and Frese, 2003). In addition, the same types of informants were chosen to keep the level of influence among the organisations constant, increasing the validity of the variables’ measurements (Glick, 1985). The surveys were mailed to the CEOs of the 575 selected firms, along with a
E. Bueno, J.A. Aragón, M. Paz Salmador and V.J. García

cover letter. We used this method because it enabled us to reach a greater number of firms at a lower cost, exercised less pressure for an immediate response and provided the interviewees with a greater feeling of autonomy. To reduce the possible desirability bias, we promised that we would keep all the individual responses completely confidential and confirmed that our analyses would be restricted to an aggregated level that would prevent the identification of any organisation.

We mailed three reminders to each CEO who have not yet responded. A total of 254 CEOs finally answered the questionnaire, but because of missing values, only 246 questionnaires were included in the research. The response rate was 42.78% (Table 1). We did not find significant differences in the type of business or the number of employees between the respondents and the sample or between the early and late responders. Furthermore, since all measures were collected in the same survey instrument, the possibility of common method bias was tested using Harman’s one-factor test (Konrad and Linnehan, 1995; Scott and Bruce, 1994). A principal components factor analysis on the questionnaire measurement items yielded five factors with eigenvalues greater than 1.0 that accounted for 75% of the total variance. Since several factors, as opposed to one single factor, were identified and since the first factor did not account for the majority of the variance, a substantial amount of common method variance does not appear to be present (Podsakoff and Organ, 1986).

Table 1  The technical details of the research

<table>
<thead>
<tr>
<th>Sectors</th>
<th>Technological firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geographical location</td>
<td>Spain</td>
</tr>
<tr>
<td>Methodology</td>
<td>Structured questionnaire</td>
</tr>
<tr>
<td>Procedure</td>
<td>Stratified sample with proportional allocation (size)</td>
</tr>
<tr>
<td>Universe of population</td>
<td>50 000 firms</td>
</tr>
<tr>
<td>Sample (response) size</td>
<td>575 (246) firms</td>
</tr>
<tr>
<td>Sample error</td>
<td>6.2%</td>
</tr>
<tr>
<td>Confidence level</td>
<td>95%, ( p - q = 0.50; Z = 1.96 )</td>
</tr>
<tr>
<td>Period of collecting data</td>
<td>From September to December 2001</td>
</tr>
</tbody>
</table>

3.2 Measures

The use of constructs has played an important role in designing a survey instrument in management research. In any research concerning behavioural elements, no device can precisely produce measurements through a single metric unit and researchers usually employ two or more measures to gauge a construct or scale. Given that developing new constructs or scales of measurement is a complex task, wherever possible, we used pretested constructs from past empirical studies to ensure their validity and reliability.

3.2.1 Technology slack

Because of their closer link with our research, good reflection of the different prior trends and detailed verification of the scale’s validity and reliability, we selected two items from the work presented by Szulanski (1996) to draw up a scale that allows technology slack
Tangible slack versus intangible resources

to be determined. We analysed the self-perception of the manager about the existence of slack (but operative) technological resources that are easily available in the organisation. Specifically, our items focused on the existence of abundant and modern equipment and technologically well-qualified human resources and of a continuous and significant amount of investment for these aspects. Our procedure is similar to the two self-report items used by Sharma (2000) to measure ‘discretionary slack’ drawn from Nohria and Gulati (1996). We verified the scale’s unidimensionality and its high validity and reliability ($\alpha = .802$).

### 3.2.2 Tacit knowledge

Of the different qualities that allow us to measure knowledge (e.g., complexity, independence), tacitness is one of the most important and has been measured from different perspectives using reliable valid scales (Hansen, 2002; Simonin, 1999; Subramaniam and Venkatraman, 2001). Using the scales established by Szulanski (1996), Zander and Kogut (1995) and Simonin (1999), which fit with the objectives pursued in our research, we drew up a scale of three items to be evaluated by the CEOs that would reflect the tacitness of their knowledge. We thus analysed whether the procedures for how to act in a specific position can be easily written, whether there are manuals on how to develop on-the-job tasks and whether the process know-how is more explicit than tacit in the organisation. The scale was unidimensional and had a high reliability ($\alpha = .839$).

### 3.2.3 Organisational learning

The capability of organisational learning has received much more theoretical attention than empirical. Additionally, there are wide differences among the assumptions, procedures and objectives of the previous measures. Due to the fact that there is a closer link with our research, that they reflected the different prior trends well and that the scale’s validity was verified in detail, we used the first two items from the scale developed by Kale et al. (2000) and added two additional items based on Edmondson’s (1999) work to compose a multi-item scale of organisational learning. These items have been duly adapted to the present study. This gave a four-item scale that measured the following issues over the last three years:

1. whether the organisation had acquired much new and relevant technological knowledge
2. whether the organisation’s members had acquired some critical technological capacities and skills
3. whether the organisational improvements had been influenced by new technological knowledge entering the organisation
4. whether the organisation was a learning organisation.

The proposed scale was similar to the other measures of external and internal learning recently proposed by Schroeder et al. (2002) and Bontis et al. (2002). We conducted a confirmatory factor analysis to validate our scales ($\chi^2 = .42$, Root Mean Square Error of Approximation or RMSEA = .00, Normed Fit Index or NFI = .99, Non-Normed Fit Index or NNFI = .99, Goodness of Fit Index or GFI = .99, Adjusted Goodness of Fit Index or
AGFI = .99, Expected Cross-Validation Index or ECVI = 0.73, Akaike Information Criterion or AIC = 16.42, Parsimony Goodness of Fit Index or PGFI = .20. The results showed that the final scale was unidimensional and had high reliability (α = .923).

3.2.4 Innovation

Numerous researchers have analysed organisational innovation using reliable valid scales that allow for its measurement (Kusunoki et al., 1998; Miller and Friesen, 1983; Verdú-Jover et al., 2005). We based our scale on Miller and Friesen’s (1983) work and defined innovation for the respondents, noting that organisational innovation, not industry or market innovation, should be their focus and asked them to evaluate innovation on products, services and production processes and to compare their firms with their competitors’. We asked them if the rate of the introduction of a new technological product/service, of the technological changes in their internal operating practices and of the technological innovations by their firms have been very high for the last three years relative to their competitors. We developed a confirmatory factor analysis to validate our scales and showed that the scale was unidimensional and reliable (α = .799). We also included questions so that the managers could offer precise quantitative data on technological innovation and innovation radicality. When possible, we calculated the correlation between the objective and subjective data and these were high and significant.

3.2.5 Performance

Having reviewed how performance is measured in different works of strategic research (Kusunoki et al., 1998; Venkatraman and Ramanujam, 1986), we drew up a scale that included six items to measure organisational performance. The managers were asked to respond to different questions: to evaluate the firm’s performance for the last three years, taken as profits over assets, as profits over sales and sales growth in the main products/services and markets. They were also asked to evaluate these questions in comparison with their principal competitors, reflecting which were above the mean. The use of scales for evaluating performance in comparison with the main competitors is one of the most widely-used practices in recent studies (Steensman and Corley, 2000).

Many researchers have used managers’ subjective perceptions to measure the beneficial outcomes for firms. Others have preferred objective data, such as the return on assets. The literature has widely established that there is a high correlation and concurrent validity between objective and subjective data on performance, which implies that both are valid when calculating a firm’s performance (Dess and Robinson, 1984; Venkatraman and Ramanujam, 1987). We included questions involving both types of assessment in our interviews, but the managers were more open to offering their general views than precise quantitative data. When possible, we calculated the correlation between the objective and subjective data and these were high and significant. We developed a confirmatory factor analysis to validate our scales ($\chi^2 = 12.53$, RMSEA = .006, NFI = .99, NNFI = .99, GFI = .99, CFI = .99, AGFI = .99, ECVI = .19, AIC = 42.53, PGFI = .28) and showed that the scale was unidimensional and had a high reliability (α = .835). We used a Likert-type seven-point scale (1 = ‘totally disagree’, 7 = ‘totally agree’) and the variables previously listed for the managers to express their level of agreement or disagreement.
3.3 Model and analysis

The LISREL 8.30 program was used to test the theoretical model. Figure 1 shows the basis of the proposed model, together with the hypotheses to be contrasted. We used a recursive nonsaturated model, taking technology slack ($\xi_1$) as the exogenous latent variable, tacit knowledge ($\eta_1$) as the first-grade endogenous latent variable and organisational learning ($\eta_2$), innovation ($\eta_3$) and organisational performance ($\eta_4$) as the second-grade endogenous latent variables. Through the flexible interplay between theory and data, this structural equation model approach bridges theoretical and empirical knowledge for a better understanding of the real world. Such an analysis allows for modelling based on both latent and manifest variables, a property well suited for the hypothesised model, where most of the represented constructs are abstractions of unobservable phenomena. Furthermore, structural equation modelling takes into account the errors in measurement, variables with multiple indicators and multiple-group comparisons.

Figure 1  The hypothesised model

4 Results and discussion

In this section, we present the main research results. First, Table 2 shows the means and standard deviations, as well as the interfactor correlation matrix for the study variables. There are significant and positive correlations among technology slack, tacit knowledge, organisational learning, innovation and performance. A series of tests (e.g., tolerance, variance inflation factor) shows the nonpresence of multicolinearity (Hair et al., 1999). Structural equations modelling (Bollen, 1989) was performed to estimate the direct and indirect effects, using LISREL with the correlation matrix and asymptotic covariance matrix as input. This type of analysis has the advantage of correcting for the unreliability of measures and also gives information on the direct and indirect paths between multiple constructs after controlling for potentially confounding variables. Figure 2 shows the standardised structural coefficients. Only the paths that are significant at the 0.5 level are shown in this diagram. The relative importance of the variables is reflected by the magnitude of the coefficients.
Table 2  The means, standard deviations and correlations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology slack</td>
<td>5.11</td>
<td>1.50</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tacit knowledge</td>
<td>4.87</td>
<td>1.49</td>
<td>.214***</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organisational learning</td>
<td>5.36</td>
<td>1.16</td>
<td>.146*</td>
<td>.291***</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Innovation</td>
<td>4.62</td>
<td>1.22</td>
<td>.274***</td>
<td>.314***</td>
<td>.609***</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Performance</td>
<td>4.93</td>
<td>1.02</td>
<td>.223***</td>
<td>.222***</td>
<td>.414***</td>
<td>.483***</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Notes:  * p < .05; *** p < .001(two-tailed).

n = 246.

Figure 2 The results of the structural equation model

Notes:  * p < 0.05; *** p < 0.001 (two-tailed).

With respect to the quality of the measurement model for the sample, the constructs displayed satisfactory levels of reliability, as indicated by the composite reliabilities that range from 0.82 to 0.94 and shared variance coefficients that range from 0.51 to 0.80 (Table 3). Convergent validity – the extent to which the maximally different attempts to measure the same concept agrees – can be judged by looking at both the significance of the factor loadings and the shared variance. The amount of variance shared or captured by a construct should be greater than the amount of the measurement error (shared variance > 0.50). All the multi-item constructs met this criterion, each loading (λ) being significantly related to its underlying factor (t-values greater than 9.68) in support of
Tangible slack versus intangible resources

Convergent validity. Likewise, a series of chi-square difference tests on the factor correlations showed that discriminant validity – the degree to which a construct differs from others – was achieved among all the constructs (Anderson and Gerbing, 1988). In particular, discriminant validity was established between each pair of latent variables by constraining the estimated correlation parameter between them to 1.0 and then performing a chi-square difference test on the values obtained for the constrained and unconstrained models (Bollen and Long, 1993). The resulting significant differences in the chi-square tests indicated that the constructs were not perfectly correlated and that discriminate validity was achieved.

Table 3  The validity, reliability and internal consistency

<table>
<thead>
<tr>
<th>Variable</th>
<th>Item</th>
<th>Parameter</th>
<th>Validity, reliability and internal consistency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology slack</td>
<td>TESLA1</td>
<td>$\lambda_{x11}$</td>
<td>0.93(f.p.)</td>
</tr>
<tr>
<td>Tacit knowledge</td>
<td>TESLA2</td>
<td>$\lambda_{x12}$</td>
<td>0.80***(9.68)</td>
</tr>
<tr>
<td></td>
<td>TACK1</td>
<td>$\lambda_{y11}$</td>
<td>0.59(f.p.)</td>
</tr>
<tr>
<td></td>
<td>TACK2</td>
<td>$\lambda_{y12}$</td>
<td>0.72***(21.38)</td>
</tr>
<tr>
<td></td>
<td>TACK3</td>
<td>$\lambda_{y13}$</td>
<td>0.97***(13.54)</td>
</tr>
<tr>
<td>Organisational learning</td>
<td>OL1</td>
<td>$\lambda_{y24}$</td>
<td>0.98(f.p.)</td>
</tr>
<tr>
<td></td>
<td>OL2</td>
<td>$\lambda_{y25}$</td>
<td>0.89***(47.29)</td>
</tr>
<tr>
<td></td>
<td>OL3</td>
<td>$\lambda_{y26}$</td>
<td>0.86***(55.05)</td>
</tr>
<tr>
<td></td>
<td>OL4</td>
<td>$\lambda_{y27}$</td>
<td>0.85***(35.95)</td>
</tr>
<tr>
<td>Innovation</td>
<td>INNOVA1</td>
<td>$\lambda_{y38}$</td>
<td>0.73(f.p.)</td>
</tr>
<tr>
<td></td>
<td>INNOVA2</td>
<td>$\lambda_{y39}$</td>
<td>0.84***(24.26)</td>
</tr>
<tr>
<td></td>
<td>INNOVA3</td>
<td>$\lambda_{y310}$</td>
<td>0.74***(21.57)</td>
</tr>
<tr>
<td>Performance</td>
<td>PERFOR1</td>
<td>$\lambda_{y411}$</td>
<td>0.68(f.p.)</td>
</tr>
<tr>
<td></td>
<td>PERFOR2</td>
<td>$\lambda_{y412}$</td>
<td>0.75***(26.14)</td>
</tr>
<tr>
<td></td>
<td>PERFOR3</td>
<td>$\lambda_{y413}$</td>
<td>0.71***(14.11)</td>
</tr>
<tr>
<td></td>
<td>PERFOR4</td>
<td>$\lambda_{y414}$</td>
<td>0.72***(14.20)</td>
</tr>
<tr>
<td></td>
<td>PERFOR5</td>
<td>$\lambda_{y415}$</td>
<td>0.75***(14.69)</td>
</tr>
<tr>
<td></td>
<td>PERFOR6</td>
<td>$\lambda_{y416}$</td>
<td>0.68***(13.76)</td>
</tr>
</tbody>
</table>

Notes: $\lambda^*$ = Standardised structural coefficient; $R^2$ = Reliability; $\alpha$ = Cronbach’s alpha; C.R. = Compound Reliability; S.V. = Shared Variance; f.p. = fixed parameter; A.M. = Adjustment Measurement; *** p < .001.

The overall fit measures, the multiple squared correlation coefficients of the variables and the signs and significance levels of the path coefficients all indicated that the model fits the data well ($\chi^2 = 218.37$, $p < .001$; $\chi^2_{\text{ratio}} = 1.93$; RMSEA = .065; NFI = .99; NNFI = .99; GFI = .99; CFI = .99; AGFI = .99). The hypothesised model was a significantly better fit than the null model ($\chi^2 = 20553$, $p < .001$; $\Delta \chi^2 = 20334.63$, $p < .001$).
All of the modification indices for the beta pathways between the major variables were small, suggesting that adding additional paths would not significantly improve the fit. The residuals of the covariances were also small and centred around zero.

If we look at the standardised parameter estimates (Table 4), the findings show that technology slack is related to and affects tacit knowledge ($\gamma_{11} = .30, p < .001$). Thus, as was predicted in Hypothesis 1, one of the essential characteristics we must consider in analysing tacit knowledge is technology slack. The pool of technological resources in an organisation in excess of the minimum necessary to produce a given level of organisational output is positively related with the existence of tacit knowledge in the organisation.

Table 4 Parameter and relationship

<table>
<thead>
<tr>
<th>Parameter and relationship</th>
<th>$\lambda^*$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Direct effects</strong></td>
<td></td>
</tr>
<tr>
<td>$\gamma_{11}$ Technology slack $\rightarrow$ Tacit knowledge</td>
<td>$0.30^{***}(5.19)$</td>
</tr>
<tr>
<td>$\gamma_{21}$ Technology slack $\rightarrow$ Organisational learning</td>
<td>$0.18^{***}(3.77)$</td>
</tr>
<tr>
<td>$\beta_{31}$ Tacit knowledge $\rightarrow$ Organisational learning</td>
<td>$0.43^{***}(9.52)$</td>
</tr>
<tr>
<td>$\beta_{32}$ Organisational learning $\rightarrow$ Innovation</td>
<td>$0.87^{***}(26.37)$</td>
</tr>
<tr>
<td>$\beta_{42}$ Organisational learning $\rightarrow$ Performance</td>
<td>$0.23^{*}(2.33)$</td>
</tr>
<tr>
<td>$\beta_{43}$ Innovation $\rightarrow$ Performance</td>
<td>$0.65^{***}(6.59)$</td>
</tr>
<tr>
<td><strong>Indirect effects</strong></td>
<td></td>
</tr>
<tr>
<td>Technology slack $\rightarrow$ Organisational learning</td>
<td>$0.13^{***}(4.37)$</td>
</tr>
<tr>
<td>Technology slack $\rightarrow$ Innovation</td>
<td>$0.27^{***}(5.95)$</td>
</tr>
<tr>
<td>Technology slack $\rightarrow$ Performance</td>
<td>$0.24^{***}(5.97)$</td>
</tr>
<tr>
<td>Tacit knowledge $\rightarrow$ Innovation</td>
<td>$0.38^{***}(9.53)$</td>
</tr>
<tr>
<td>Tacit knowledge $\rightarrow$ Performance</td>
<td>$0.34^{***}(7.88)$</td>
</tr>
<tr>
<td>Organisational learning $\rightarrow$ Performance</td>
<td>$0.56^{***}(6.35)$</td>
</tr>
<tr>
<td><strong>Total effects</strong></td>
<td></td>
</tr>
<tr>
<td>Technology slack $\rightarrow$ Organisational learning</td>
<td>$0.31^{***}(6.52)$</td>
</tr>
<tr>
<td>Technology slack $\rightarrow$ Innovation</td>
<td>$0.27^{***}(5.95)$</td>
</tr>
<tr>
<td>Technology slack $\rightarrow$ Performance</td>
<td>$0.24^{***}(5.97)$</td>
</tr>
<tr>
<td>Tacit knowledge $\rightarrow$ Innovation</td>
<td>$0.38^{***}(9.53)$</td>
</tr>
<tr>
<td>Tacit knowledge $\rightarrow$ Performance</td>
<td>$0.34^{***}(7.88)$</td>
</tr>
<tr>
<td>Organisational learning $\rightarrow$ Performance</td>
<td>$0.79^{***}(15.04)$</td>
</tr>
</tbody>
</table>

Notes: $\lambda^*$ = Standardised structural coefficient; *$p < 0.05$; **$p < 0.001$ (two-tailed).
As predicted in Hypothesis 2, organisational learning appears to be strongly influenced by technology slack ($\gamma_{21} = .18$, $p < .001$). Furthermore, we have shown an indirect effect (.13, $p < .001$) of technology slack on organisational learning due to tacit knowledge (.30 × .43; for calculation rules, see, for instance, Bollen (1989)). The global influence of technology slack on organisational learning is thus 0.31 ($p < .001$). Organisational learning appears to be strongly influenced by tacit knowledge ($\beta_{31} = .43$, $p < .001$), supporting Hypothesis 3. Comparing the magnitudes of these effects indicates that the effect of tacit knowledge on organisational learning is larger than the effect of technology slack on organisational learning.

The indicated results also support Hypothesis 4, showing that innovation is also affected by organisational learning ($\beta_{12} = .87$, $p < .001$). As previously mentioned, much earlier research has demonstrated this relation. Finally, Hypotheses 5 and 6 relate organisational learning and innovation to organisational performance. Hypothesis 5 holds because the parameter estimates verify a positive and statistically significant association between organisational learning and performance, both directly ($\beta_{42} = .23$, $p < .05$) and indirectly by innovation (.56, $p < .001$). The total effect (direct and indirect) of organisational learning on performance is 0.79 ($p < .001$). The positive significant relationship between innovation and performance ($\beta_{43} = .65$, $p < .001$) supports Hypothesis 6. Of these two variables (organisational learning and innovation), organisational learning has shown the greatest influence on organisational performance.

In addition to these effects, we have shown an indirect effect (.27, $p < .001$) of technology slack on innovation by tacit knowledge-organisational learning (.30 × .43 × .87) and organisational learning (.18 × .87). Likewise, there is an indirect effect (.24, $p < .001$) of technology slack on performance by tacit knowledge-organisational learning (.30 × .43 × .23), tacit knowledge-organisational learning innovation (.30 × .43 × .87 × .65), organisational learning innovation (.18 × .87 × .65) and organisational learning (.18 × .23). Tacit knowledge has an indirect effect (.38, $p < .001$) on innovation by organisational learning (.43 × .87). Finally, tacit knowledge has an indirect effect (.34, $p < .001$) on performance by organisational learning (.43 × .23) and organisational learning-innovation (.43 × .87 × .65).

In testing the theoretical framework, we fit several nested models, each incorporating different assumptions about the parameters. Comparisons with reasonable alternative models are recommended as a means of showing that a hypothesised model is the best representation of the data. Comparison is considered to be an important part of assessing model fit (Bollen and Long, 1993). The summary statistics in Table 5 indicate that Model 1 is preferable to the others, supporting the inclusion of a model with these relationships among the analysed constructs. For example, if we compare the theoretical model (Model 1) with a model that does not consider the relationship between organisational learning and innovation (Model 4), we can see that the latter has a worse RMSEA (RMSEA = .044), NFI (NFI = .01), NNFI (NNFI = .01), GFI (GFI = .01), AGFI (AGFI = .02), ECVI (ECVI = .86), AIC (AIC = 186.98) and Estimated Non-centrality Parameter or NCP (NCP = 186.98). Hence, the results show that organisational learning affects innovation and that Model 1 is preferable to Model 4 ($\Delta \chi^2 = 186.98$, $\Delta df = 1$). Likewise, we see that the theoretical model is preferable to the remaining models formulated (Table 5). Length restrictions prevent a detailed discussion of each model and of other models (a full report is available from the authors).
### Table 5
The parameter, relationship and goodness of fit statistics

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>$\chi^2$</th>
<th>df</th>
<th>$\Delta \chi^2$</th>
<th>RMSEA</th>
<th>NFI</th>
<th>NNI</th>
<th>GFI</th>
<th>CFI</th>
<th>AGFI</th>
<th>ECVI</th>
<th>AIC</th>
<th>PGFI</th>
<th>NCP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Theoretical</td>
<td>218.37</td>
<td>113</td>
<td></td>
<td>0.065</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>1.53</td>
<td>334.37</td>
<td>0.65</td>
<td>105.37</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>W.R. Technology slack $\rightarrow$ Organisational learning</td>
<td>231.67</td>
<td>114</td>
<td>13.3</td>
<td>0.069</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>1.59</td>
<td>345.67</td>
<td>0.66</td>
<td>117.67</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>W.R. Tacit knowledge $\rightarrow$ Organisational learning</td>
<td>324.58</td>
<td>114</td>
<td>92.91</td>
<td>0.092</td>
<td>0.98</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td>2.01</td>
<td>438.58</td>
<td>0.66</td>
<td>210.58</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>W.R. Organisational learning $\rightarrow$ Innovation</td>
<td>405.35</td>
<td>114</td>
<td>186.98</td>
<td>0.109</td>
<td>0.98</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>2.39</td>
<td>521.35</td>
<td>0.65</td>
<td>292.35</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>W.R. Organisational learning $\rightarrow$ Performance</td>
<td>222.48</td>
<td>114</td>
<td>4.11</td>
<td>0.066</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>1.54</td>
<td>336.48</td>
<td>0.66</td>
<td>108.48</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>W.R. Innovation $\rightarrow$ Performance</td>
<td>246.82</td>
<td>114</td>
<td>28.45</td>
<td>0.073</td>
<td>0.99</td>
<td>0.99</td>
<td>0.99</td>
<td>0.98</td>
<td>1.66</td>
<td>360.82</td>
<td>0.66</td>
<td>132.82</td>
<td></td>
</tr>
</tbody>
</table>

Notes: W.R. = Without Relationship; n = 246.
5 Conclusion

This investigation serves as a reference for technological firms. In this world of knowledge and technology economy, tacit knowledge and technology slack are key issues for these firms. These factors will allow firms to maintain their competitive positions as technological centres, to become more learning organisations and to be technologically innovative, producing greater organisational performance.

First, we verified the existence of a relation between technology slack and organisational learning. The existence of a pool of technological resources in an organisation in excess of the minimum necessary to produce a given level of organisational output encourages organisational learning probably through multiple ways (such as the existence of a munificent climate that allows employees to research and experiment or the availability of technological resources in their own department). Managers use technology slack to enable the clear formulation of the global strategy that is necessary in the long term for the organisational learning focus. Even so, we must be cautious of the existence of the superabundance of slack that may erode the competitive tension of the organisation (Nohria and Gulati, 1996). Our findings are useful inside of the regular levels of technological slack, as those showed in the sampled firms.

Managers must take into account that the management of all the organisation’s value added technological activities should be supported by the strategy and internal and external technological resources of the organisation. From the perspective of organisation theorists, the benefits of technology slack outweigh its costs and a zero technology slack organisation is not realistic. Thus, this paper maintains that organisational learning is determined and limited by the nature and variety of technological resources that the organisation can bundle and apply to the maintenance and development of technological competitive advantages (Pack, 2000).

Second, we showed the critical role played by tacit knowledge in technological firms. This tacit knowledge significantly influences organisational learning. Organisational learning is determined by the totality of beliefs, ideas, values and mental schemas (cognitive tacit knowledge), which affect the ability to perceive reality and learning. Organisational learning is also determined by existing skills and capabilities (technical tacit knowledge). Tacit knowledge is essential to mental models or schemas. The schemas determine how we understand and analyse situations, how we understand cause-effect connections and how we learn (Lubit, 2001).

Third, we empirically demonstrated that technology slack and tacit knowledge influence the whole system of organisational learning. Firms facing real situations of crisis and technological uncertainty should undertake the development of technological knowledge through investments in learning and an increase in the effort to learn. We should encourage learning that enables the internal and external analysis of the existing technology, technological reflection and the storing of this knowledge in organisational memory, the dissemination of the acquired and learned technological knowledge, technological decision-making and the implementation of the chosen technological options (García-Morales, 2004). The firm’s directors should exercise their role as mentors by using resources and creating systems of work in the organisation and a culture that favours technological development (García-Morales, 2004). There is no universal sequence to follow in realising organisational learning, but different authors recognise the
importance of tacit knowledge and technology slack for enabling the resources, assets and technological abilities needed to foster the learning spirit (Nonaka and Takeuchi, 1995; Senge, 1990).

Fourth, we empirically showed that in technological firms, organisational learning enables the capacity to realise innovations. An innovative organisation is an organisation that learns and knows how to make and keep itself technologically competent. Learning will enable the organisation to change its behaviour and, thus, to renew and reinvent itself technologically, preventing it from falling into technological stagnation and allowing it to generate innovation. Different organisations will find themselves in different states of evolution in learning. The sooner measure diffusers are encouraged, the less complicated the leap to innovation will be (Bessant and Buckingham, 1993; Glynn, 1996).

Fifth and finally, we empirically verified that more organisational learning and innovation generate better organisational performance in technological firms. The sources for achieving sustainable competitive advantages in technological firms are really sustained by the existence of a complex of essential technological competencies or the resources and technological capacities that organisations possess. Each organisation should analyse and enable the whole of its own technological resources, the resources that permit it to obtain a better competitive position on the market. It should also develop its specific capacities and regenerate its essential competences so it can face the technological changes in its environment. To this end, it should encourage organisational learning and innovation. Thus, the organisation acquires a dynamic and proactive vision that enables it to improve its organisational performance, generating for itself resources and technological capacities that are unique, valuable, hard to replace and not easily imitated. Two of the main variables that determine organisational performance in technological firms are, thus, organisational learning and innovation, both with positive causal effects. Both dynamic capabilities are strategic and should be encouraged (Calantone et al., 2002; Stephan et al., 2000).

We must generalise cautiously from our results. This study has several limitations that may suggest further possibilities for empirical research. First, the survey data based on self-reports may be subject to social desirability bias (Scott and Bruce, 1994). However, an assurance of anonymity can reduce such a bias, even when the responses relate to sensitive topics (Glick, 1985). The low risk of social desirability bias in this study was indicated by several managers who commented at the end of their questionnaires that it made no sense at all for their companies to go beyond regulatory compliance. Still, the responses are subject to interpretation by individual managers.

Second, the external validation of some of the variables (e.g., organisational performance, innovation) from the archival data of a subset of respondents increased confidence in the self-reports and reduced the risk of common method variance. Furthermore, the possibility of common method bias was tested using Harman’s one-factor test and no such bias appears to be present (Glick, 1985; Konrad and Linnehan; 1995; Scott and Bruce, 1994).

Third, the cross-sectional nature of the research into a series of dynamic concepts (innovation, organisational learning) allows us to analyse only a specific situation in the time of the organisations studied, not their overall conduct over time. Our approach has reduced the magnitude of this problem, however, for the items reflect dynamic characteristics. Causal affirmations can be made if the relationships are based on
theoretical rationales (Hair et al., 1999). This is why we began with a theoretical effort that allowed us to identify and check the formal existence of the different cause-effect relationships. Nonetheless, future research should focus on a longitudinal study.

Fourth, the use of a single respondent could have influenced the accuracy of some measurements. The difficulties in obtaining sponsorship for research based on multiple views for each firm, the lack of an alternative database of organisational characteristics for the Spanish firms, the value of the CEOs’ knowledge of their firms and common practice in organisational research all supported the use of CEOs as respondents.

Fifth, our results must be cautiously analysed in view of the geographical peculiarities of our sample. Future studies should be based on a larger sample, preferably in more than one country.

Sixth, the conclusions established by our study should be interpreted with care when generalising, since we have concentrated exclusively on the technological sector. In the firms from other sectors, the results may be different.

Finally, our model only analyses technology slack and tacit knowledge, factors that have been strategically recognised as main catalysts in the organisational learning and innovation process. Others could be analysed, such as technology-shared vision and technology teamwork (Senge, 1990; Senge et al., 1994). However, it should be noted that these strategic variables (technology slack and tacit knowledge) explain a significant amount of variance of organisational learning, innovation and performance. We should also examine the other consequences of introducing an organisational learning and innovation process in technological firms (e.g., quality improvement, staff satisfaction, improvements in the relational capacity). Empirical papers supporting (or rejecting) our results in different contexts would be welcomed (especially longitudinal studies). It would also be interesting to study similar characteristics, with information provided by the lower levels of management and employees of the organisation.

Acknowledgement

We would like to thank all the managers who contributed their time and ideas to this study. Project SEC 2003-07755 and Foundation BBVA partially supported this research.

References


