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Abstract - This paper explores ongoing debates about the role that codified forms of knowledge play in fostering firms' and countries' innovative performance. It aims to provide an empirical exploration of the use of codified sources of information for innovation at the sectoral level. Despite considerable interest in David and Foray's (1995) work on the codification of knowledge and the changing nature of innovation due to the use of information and communication technologies, there are relatively few empirical studies that probe the role of codified sources of information in the innovation process. Our goal is to assess 'how' important codified sources of information are for innovation for different sectors and to the innovation system in general. We explore the relationship between the use of codified sources by individual firms and increases in the 'distributional power' of an innovation system, a key component in David and Foray's codification argument. We then link the use of codified sources to different innovative strategies and characteristics of innovation at the firm level. The data used for the analysis is based on The Netherlands Community Innovation Survey (II) for the manufacturing sector. The data set covers 1997 firms in 11 major industries.

Keywords: Innovation, knowledge, manufacturing industries, codification
JEL number: L60, O32, O33

1. Introduction

The relationship between processes of knowledge codification and innovative activities has attracted much attention in recent years[i]. Practitioners are interested in assessing the effectiveness of tools to produce, gather, structure and distribute information and knowledge. Policy makers need to evaluate the impact of investments in the new electronic infrastructure on the innovative performance of industries and countries. Academics are confronted by an increasing number of questions related to the changing nature of knowledge, and its economic role, in response to the information and communication technologies (ICT) revolution.

The ICTs revolution sparked an outburst of research focused on the causes, consequences and policy implications of processes of knowledge production and distribution. Throughout the last decade, one of the most visible and interesting lines of reasoning concerns the analysis of how knowledge can be characterised and how its characteristics relate to the activities underpinning innovative performances. In particular, the distinction between tacit and codified knowledge has played a pivotal role in this discussion. Tacit knowledge refers to the inarticulable contextual framework(s) that provides individuals' cognitive processes with the background within which to focus on, and attribute meaning to, conditional statements. It is often referred to as 'know how'. Codified knowledge refers to the availability of messages and generic algorithms that can be easily and (relatively) cheaply transmitted and deployed in a context other than that in which they were originated. It is often referred to as 'know what'.

[i] The empirical part of this research was carried out at the Center for Research of Economic Microdata at Statistics Netherlands. The views expressed in this paper are those of the authors and do not necessarily reflect the policies of Statistics Netherlands.

In this paper, we provide an empirical exploration of the relationship between the use of codified sources of information for innovation and the innovative strategies of Dutch manufacturing firms. The analysis of this relationship is broken down in three parts. First, we assess the importance of codified sources of information for innovation at sectoral level. Second, we explore the relationship between the use of codified knowledge and the different innovative strategies. Finally, we explore the link between codified sources and innovative performance. The empirical analysis is based on the Community Innovation Survey (CIS 2) of Dutch manufacturing.

The data shows that innovative firms in Europe relatively infrequently use codified sources of information for innovation. Evidence from Dutch manufacturing suggests that those firms that rely on codified sources of innovation also invest heavily in research and development. This suggests that accessing codified sources is expensive. The econometric analysis of firm-level patterns shows that the use of codified sources is significantly correlated to the use of other parts of the innovation system. This suggests that the degree of "embeddedness" of firms in the innovation system can help to explain their use of codified knowledge. The econometric data, however, shows little relationship between innovative performance and the use of codified knowledge.

This paper is organised as follows. Section 2 reviews a few contributions regarding the role played by codified sources of information in the innovation process. Section 3 describes the method of our study. Section 4 reports on the empirical analysis and Section 5 contains the conclusions and policy implications.

2. Theoretical background

The economic analysis of knowledge as a specific input to innovative activities has been approached following two – largely independent – methodological approaches. On the one side, economists have characterised knowledge in very abstract and generic terms. Knowledge is seen as a public good generated via R&D activities that generate spillovers and thus increasing returns (Romer, 1994; Grossman and Helpman, 1994). While delivering useful insights regarding the determinants of dynamic comparative advantages at country level, this approach does not deliver an adequate understanding of the specific processes through which new knowledge is generated. It also does not explore what types of knowledge are generated through which processes, how different types of knowledge are transferred and how they actually affect the innovative opportunities of recipients.

Langlois (2001) raises doubts as to the usefulness of pinpointing the 'public good' properties of codified knowledge as the main source of spillovers that generate system-wide increasing returns. He argues that knowledge is not often characterised by public- or club-good characteristics, and that the strong assumptions about the public good character of knowledge are not necessary to explain the 'reuse of knowledge' (p. 83). Knowledge, whether tacit or codified, is embodied in institutions and artefacts that make its transfer possible even in the absence of any codification effort.

Scholars in innovation management have relied on in-depth case studies in order to disentangle the specific processes underlying the generation and diffusion of information and knowledge within specific organisational contexts (Leonard-Barton, 1995; Pisano, 1997).

This stream of literature provides an insightful analysis that identifies the key relationships to be analysed, the specific channels that link various types of knowledge to innovative performance, the means and obstacles to transfer knowledge in different contexts. This literature (although providing results that are, *per se*, hardly generalisable) has been able to identify key characteristics of knowledge that can, in principle, be measured. So, for instance, knowledge can be abstract and general as opposed to applied and specific, tacit as opposed to codified, scientific as opposed to technological.

On this basis, a few studies have statistically addressed the impact of some specific attributes of knowledge on innovation. For instance, Breschi, Malerba and Orsenigo (2000) empirically assessed the role played by (among other things) different types of knowledge in connection with different types of technical change or, more precisely, technological regimes. In particular, they considered the dichotomy between specific and generic knowledge. The former refers to 'knowledge specialised and targeted to specific applications' and it is generated by 'applied science', i.e. research activities that 'respond to problems generated by practical experience' (p. 392). The latter refers to 'knowledge of a very broad nature' and it is generated by 'basic science' that aims at delivering 'general understanding' (p. 392). They found that the increasing availability of generic knowledge is positively associated with a 'deepening' pattern of innovative activities, characterised by the dominance of a few firms that innovate relying on processes of creative accumulation of capabilities. Conversely, specific knowledge is associated with a 'widening' pattern of innovative activities, characterised by the continuous enlargement of the innovative base via entry of new firms and the erosion of the advantages of incumbents.

At a more abstract level, Arora and Gambardella (1994) argued that advances in 'theoretical understanding of problems, instrumentation, and computational capability' (p. 525), have given impetus to the use of general and abstract knowledge. Abstract knowledge is understood as the ability to represent phenomena in terms of limited number of essential elements, whereas general knowledge is described as knowledge that relates the outcome of a particular experiment to the outcome of other, more 'distant' experiments. They argued that the increasing availability of easily transmissible general and abstract knowledge would improve firms' innovative performance enhancing their capabilities to explore wider design spaces, through designing cheaper as well as more accurate experiments.

Dasgupta and David (1994) drew attention to the institutional arrangements that enable and push agents to produce more codified/generic knowledge, and then distribute it. In particular, Dasgupta and David (1994) discussed at length the epistemological and policy implications of the distinction between codified and tacit knowledge. On the epistemological side, they rejected the possibility of granting technological knowledge (i.e. tacit/specific knowledge) an autonomous epistemological status from scientific knowledge (i.e. codified/general knowledge). They acknowledged the need to better understand the relationship between them in order to maximise the efficiency of the transfer mechanisms that allow private enterprises to benefit from academic research. Thus, on the policy side, they stressed the need to better assess the means and incentives that determine the extent to which codified (as opposed to tacit) knowledge is produced and then circulated. Therefore, the aim of modern science policies should be to foster the distribution of knowledge between research centres and industry in order to support the overall system's innovative performance.

David and Foray (1995) analysed the relationship between codification and innovative performance. Similarly to Arora and Gambardella, they stressed the role played by 'computer-aided design, testing and experimentation … as the primary tool for the development of new products and processes' (p. 43). In particular, they argued that codified sources of knowledge are becoming increasingly important in the innovation process. The codification process involves the reduction and conversion of information that renders its transmission, verification, storage and reproduction of information less costly. They suggested that codified information "require[s] less resources to preserve for retrieval" (David and Foray, 1995). In their view, the increasing codification of the knowledge stock would enhance firms' innovative performance in two related ways. First, it would bring 'science into tighter and quicker interaction with technology' (p. 43), thus allowing each to fully benefit from the other's developments. Second, formalisation would increase the pace of product and process innovation by reducing the reliance of rules of thumb in favour of more precisely defined experimental conditions.

In order to explain the relationship between codification and innovative performance, David and Foray (1995) introduced and discussed the notion of 'distributional power' of a science and technology system. They pointed out that much of the existing literature on innovation focuses on only one-way of 'improving the performance of a system of science and technology learning: increasing the stock of knowledge' (p. 23). They contended that it is also important to consider the parallel problem represented by the characteristics of the *distribution* system of information and knowledge. In this respect, they defined the 'distribution power' of an innovation system as its 'ability to support and improve the efficient functioning of procedures for distributing and utilising knowledge' (p. 22). In their view, an efficient system of 'distribution and access … will increase the social value of both the knowledge that is being produced [in house] … and [that] acquired and assimilated from external sources' (ibid.). It would do so by increasing the chances to produce new and better combinations by putting 'information into the hands of a more diverse population of researchers' (ibid.).[i]

In summary, David and Foray (1995) argued that the ICTs revolution is making codified forms of knowledge more commonly available than ever before. The increasing availability of codified knowledge enhances the distributional power of the innovation system. In turn, this raises the innovative performance of the system. They also note that this model could break down for a number of reasons (David and Foray, 1995: 41). First, high access costs to the relevant information networks would limit agents' search space. Second, a great deal of knowledge is tacit. Third, ill-designed property rights may limit distribution. Fourth, the transfer of knowledge (even though codified) may be hindered by the existence of institutions and communities that rely on incompatible rules of disclosure, goals and reward structures.

Bearing this in mind, in the next section we propose a method for exploring the relationship between the use of codified knowledge and the innovative strategies of Dutch manufacturing firms. In order to do so, we empirically explore some of the elements of the above

[i] David and Foray's approach and many of the studies of innovation systems are unclear about what are the *systematic* properties of the system. Considerable effort has been made to suggest that innovation systems are more than just a list of institutions and actors, but rather a series of interactions between actors involved in the development and diffusion of innovations across a national economy (See Lundvall, 1992 and Edquist, 1997).

discussion on the relationship between the use and availability of codified knowledge, distributional power of a system and innovation. First, relying on the results of the second Community Innovation Survey, we assess the importance of codified knowledge for Dutch manufacturing firms.

Second, we try to operationalise and measure two relationships that lie at the core of the literature on codification. The first relationship impinges upon the notion of 'distributional power'. In particular, we estimate the relationship between codification and the ability of firms to exploit external sources of information and knowledge. The second relationship focuses on the link between codification and innovative performance. In particular, we estimate the relationship between codification and the innovative performance of firms in the Dutch manufacturing sectors. In both cases, the literature reviewed above led us to expect a positive relationship. The next section discusses the indicators used to measure the reliance of firms on codified forms of knowledge. Subsequently, the econometric model we use in the second part of the empirical analysis is presented.

3. Research Method

Despite the interest in codification in the innovation literature, few empirical studies have attempted to empirically explore the extent and use of codified knowledge across different industries. There are few direct measures of codification and therefore, proxies need to be designed. David and Foray (1995) provided a number of suggestions in terms of what factors one should look at in order to assess the availability of forms of codified knowledge and the efficiency of the system's distributional power. In particular, they highlighted the role of three key variables. First, government-supported *information networks* (which carry and distribute codified knowledge) can be used as a proxy to capture the extent to which firms rely on codified forms of knowledge.[ii] Second, the reliance on *scientific papers* as a means to access externally generated 'general and abstract' knowledge can also be associated with the increasing importance of codified forms of knowledge. Finally, the use of *patents disclosure* mechanisms can also be read as a proxy to assess the importance of codified knowledge to firms.

In fact, all of these proxies were listed in David and Foray's paper, which was written for the OECD to support the development of the Community Innovation Survey and surveys of innovation in Canada, Australia and Japan, appear in the Community Innovation Survey. In developing the model of the innovation survey, the idea of exploring the information sources for innovation was widely acknowledged to be a key area for collecting information on innovation. David and Foray's work played a pivotal role in shaping the new innovation survey questionnaire.

Our analysis is based on the data from the Community Innovation Survey 2 on Dutch Manufacturing. The selection of the Netherlands as the country of analysis was made on the basis of the availability of data. A similar analysis for different European countries using CIS data would provide an opportunity to extend our approach more widely. The choice of the Netherlands is a fortunate one, however. Although the Netherlands economy is generally considered to be one of the better performing European economies through the 1990s, the Netherlands economic statistics place close to the average among OECD countries across a

[ii] The European Commission as well as other OECD governments have supported programmes that enhance the access to information for industrial firms (European Commission, 2001). These programmes

range of variables. For example, the Netherlands spends close to the OECD average on research and development and for business funded R&D (Salter and D'Este et al. 2000). Furthermore, the high quality of the statistics available for the Dutch economy allows this study to be put into a wider research context. For instance, Den Hertog *et al.* (1995) carried out one of the early exploratory studies aimed at assessing the distribution power of the Dutch innovation system. They argued that a number of policies were already in place to remove some of the factors that David and Foray (1995) argued might hinder the development of a proper innovation system. The relatively small size of the Dutch economy should support the efficacy of these policies and thus the access of firms to relevant information networks, an homogeneous regime of property rights and the establishment of agreed, or at least not inconsistent, rules of disclosure.

In this context, the managers from Dutch manufacturing firms were asked to rate the importance of thirteen possible sources of externally generated information and knowledge. Among these thirteen sources, only two of the thirteen sources can be considered to explicitly represent codified knowledge: patent disclosures and computer-based information networks. Publications are obviously a source of codified knowledge, yet the innovation survey lists publications alongside conferences. Conferences cannot intuitively be considered a codified source of information since they often involve considerable face-to-face interaction and therefore it is not possible to use responses to this question for the analysis. Therefore, we have developed a proxy measure for the importance of codified knowledge relying on 'information networks' and 'patents disclosure'.

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include attempts to support information dissemination of scientific research, on-line patent databases and funding for computer-based information networks.

Our proxy measure for codification is a combined score for each firm on the importance of patent disclosure and computer-based information networks. In the survey, firms were asked to respond on a 0-1-2-3 Likert scale with 0 being not at all important and 1-2-3 representing somewhat important, important and very important. For each firm, we estimated a codification score with the maximum score of 6 and a minimum score 0. A number of statistical problems are associated with the use of Likert-scale survey responses in the construction of the index. The most important concerns the use of categorical response data as if they were interval data. As in previous studies (Cohen, Levin and Mowery, 1987; Klevorick *et al.*, 1995a), we assume that in the absence of alternative quantitative measures the response categories provide as first approximation numerical values for the importance of the source of information.

Although our proxy measure does not represent the full extent of codification, it does provide an operational proxy of it. Moreover, it provides a starting point for an empirical study of the framework proposed by David and Foray. Greater methodological refinement and empirical analysis will be required to further develop this line of research.

Data for the analysis is drawn from the second Dutch Community Innovation Survey (CIS 2) carried out by Statistics Netherlands[iii]. The survey was held in the entire private sector and covers the years 1994-1996. The population is defined by all firms with at least 10

[iii] The main results of the second Dutch Community Innovation Survey are presented in Klomp and Van Leeuwen (1999) and Statistics Netherlands (1998).

employees[iv]. For the population of manufacturing firms, which is the object of analysis of this paper, a total of 3299 responses were obtained with a response rate of 71 per cent. This represents the 32 per cent of the population of Dutch manufacturing firms. Among this population, we analyse responses of innovators. There are 2205 innovators in the sample.

Throughout the analysis, individual responses are weighted by a factor that was constructed by researchers at Statistics Netherlands in order to account for the different sampling of firms. This factor, stratified according to the SIC 2-digit sector, size class and region, allows generation of the survey sample estimates for the entire population of firms in the manufacturing sector and across industrial sectors.

The sectoral indicators used in the analysis are defined for two different levels of aggregation of the original SIC 6-digit industries available in the survey. The reason for aggregation is to obtain a sufficient number of firms represented in each sector so as to average out measurement errors related to individual effects. For the analysis of the relationship between codification and innovation investment indicators, an aggregation of industries into 12 sectors was first defined. From this a second classification of 62 sectors was derived, for which the pattern of codification and innovation investment across sectors is illustrated in greater detail[v]. The econometric analysis is at the firm level and based on 11 different sectoral estimations. This aggregation was required to ensure a reasonable number of responses for the sectoral estimations.

[iv] The selection of the population extends the EUROSTAT standard, in which the lower band for the inclusion of manufacturing firms is set at 20 employees.

[v] In the survey a number of firms, mainly large corporations, are classified at two-digit or three-digit level only. Therefore 13 respondents, for which the available SIC code was not consistent with the level of aggregation used in the analysis, are excluded from the construction of the sectoral indicators.

4. Empirical findings

4.1 Sectoral patterns

In this section, we explore the use of codified sources of information for innovation. Data from the CIS 2 shows the importance of various sources of information for innovation across countries. Table 1 shows the percentage of innovative firms in each CIS country that rated each source as very important. It shows that *sources within the enterprise* was the most highly rated source of information for innovation among innovative firms in Europe. Although the CIS 2 did not list the types of sources that are important inside the enterprise, past innovation surveys have shown that it was the internal divisions that were important. They included: research and development, design, sales and marketing and senior management (See Baldwin and Da Pont, 1996). Among external sources the most important were customers, enterprises within the enterprise group and fairs and exhibitions. Further down the list of sources were computer-based information networks and patent disclosure. Only 4 % of innovative firms in the CIS 2 rated these sources as a very important source of information for innovation (OECD, 1999).

Insert Table 1

The findings from the CIS 2 are mirrored in the results of the CIS 2 on Dutch manufacturing. Among Dutch manufacturing firms, the key sources of information for innovation are sources within the enterprise, clients or customers, conferences and publications and fairs and exhibitions. Only 18 % and 20 % of firms cited computer-based information networks and patent disclosures respectively. This suggests that few firms find codified sources of innovation as an important source of information for innovation. A minority of innovative firms used codified sources of information for innovation. Even among firms that did cite codified sources, these sources were relatively unimportant in comparison to other sources of information for innovation. For example, among Dutch Manufacturing firms, only 35 firms out of 1997 in the database listed both of these sources as “very important”.

There are some differences between the responses of firms from the Netherlands and other European firms. Overall, firms from the Netherlands cited fewer sources than firms from other European countries. In particular, a significantly lower proportion of the firms indicated that clients were very important. Firms from the Netherlands also granted less importance to fair and exhibitions and to competitors. These findings are consistent with other studies of the results of CIS 2 data that suggest considerable variation across countries in the style and magnitude of responses.

Insert Table 2

The data also shows that industries differ in the extent to which they rely on codified sources of knowledge. This evidence is consistent with Winter’s argument that manufacturing industries differ in the characteristics of the ‘knowledge environment’ in which firms operate. Cross-sectors differences in the nature of the knowledge bases are important as they influence the organisation of innovative activities and the knowledge-related strategic choices of firms in different industries (Winter, 1987).

Table 3 explores rates of codification by sector. This data is based on average aggregate scores for 12 industries. It is immediately apparent that the codification is strongest in science-based sectors, especially chemicals and electrical and optical equipment. The level of use of codified sources is also high for machinery and equipment. The lowest users of codified sources are textiles and leather, fabricated metal products and publishing and printing. The higher percentage of codified users mirrors the average codification score. Overall, less than half the sample of firms use codified sources of information for innovation. Only in chemicals is the percentage of users of codified sources above half of the population. The use of codified sources is positively associated with R&D intensity (0.600, p-value equal to 0.039). There are some exceptions here. Both food and transportation have relatively high R&D intensities, but low or modest levels of codification.

The data shows that there are significant industrial differences in the use of codified sources. This suggests a sectoral approach is required to understand the detailed relationships between codification and firm-level innovation. It also indicates the need to understand how different industries use sources of information to shape their innovation processes. There is no single pattern use of sources of information for innovation, therefore we should expect to find differences across sectors in the regressions.

Insert Table 3

In order to further the analysis, we performed a correlation matrix between the level of codification and the level of investment in innovation, such as R&D, R&D personnel and innovation expenditure. The correlation matrix is based on the 62 industries, as described in

Section 3. Using this industry-level, we found that there was a strong positive relationship between codification and R&D intensity as a percentage of sales at the level of the industry. We also found a strong positive relationship between the percentage of R&D personnel employed in an industry with those industries with high levels of codification. The correlation between the intensity of innovation expenditure on sales was not significant. Innovation expenditure includes expenditures on industrial design, marketing, skills and training and capital equipment.

Insert Table 4

The results of the correlation analysis suggest that there is a strong positive relationship between the codification of the knowledge base of the industry and its investment in skilled people and R&D. To realise the advantages of the codification, industries need to have a sufficient level of investment. Our evidence suggests that even when the knowledge base of an industry is highly codified, firms still need to make significant investments in their absorptive capacity to access and acquire codified knowledge. This is consistent with previous analysis (Cohen and Levinthal, 1989). Our analysis suggests that codified knowledge can be expensive to access and use. Investment in technology and new equipment (as represented here by innovation expenditure) may not be sufficient to allow firms to access codified sources of information. This is demonstrated by the lack of correlation between codification and industrial equipment, which seems to be at odds with part of the arguments of Langlois (2001), who stresses the role played by artefact-embodied knowledge. In other words, although codified knowledge can be considered a public good, it is an expensive one.

There are a number of theoretical reasons why levels of codification in an industry may be correlated to high levels of investment in tacit skills. As Winter (1987) has suggested tacit and codified need not be substitutes. They can be seen as complements in the learning process. Our data suggests that investment in tacit skills, as evidenced by R&D personnel, helps to facilitate access to codified sources of knowledge.

4.2 Codification and firm-level innovation

In this section, we explore the link between the use of codified sources and the distribution power of the innovation system. As we mentioned above, the use of codified sources of information is a property of a minority of firms and the rates of use of codified sources vary considerably between different sectors. We also found that levels of investment in R&D play a key role in shaping the degree of codification at the sectoral-level. In this section, we explore these patterns in greater detail and at the firm level.

Our objective is to estimate the contribution of the firm-specific innovation characteristics to the use of codified knowledge by the firm. Following Winter (1987), we accept that different industries are characterised by different ‘knowledge environments’. Also, since codified and tacit knowledge do not seem to be substitutes, the extent to which firms rely on one or the other is also a matter of strategic choice. For instance, Singh and Zollo (1998) analysed in detail the ‘codification strategy’ of a number of firms in the banking industry to argue that diminishing returns also apply to investment in codification. In other words, the competitive environment, accumulated capabilities and the strategy of the firm need to be considered when assessing the extent to which codified sources of knowledge are examined.

We try to take into account the variety in firms' strategies toward codification by relying on CIS data. Innovation taxonomies (Pavitt, 1984; Marsili, 2001) have highlighted a number of distinctive features that identify clusters of firms and industries according to their distinctive approaches to innovation. Such different clusters are usually described in terms of differences in the sources of innovation, the prevalence of alternative types of innovation (e.g. product vs. process innovation, autonomous vs. systemic innovation), the reliance on external sources of embodied or disembodied knowledge, and so forth. In the following, we rely on the methodology developed by Marsili (2001) and the CIS data for Dutch manufacturing to identify a set of indicators that provide some link between different innovative strategies and the use of codified sources of information.

As said above, the use of codified knowledge is measured by the codification score (CODSCORE) of the firm. Since this is derived as a combination of multinomial-choice variables and it is ordered from a minimum score of 0 to a maximum score of 6, we specify an ordered logit model. We assume that there is a latent dependent variable measuring codification, y_i^*, which is given by the equation:

$$y_i^* = b\,\mathbf{X}_i + \varepsilon_I \qquad (1)$$

with b a vector of parameters to be estimated, $\mathbf{X}_i$ a vector of explanatory variables for firm *i*, and ε_i an error term. The actual measure of codification y_i^* is unobserved. Therefore, the observed codification score y_i has to be used for the model estimation. The relationship between the two variables is expressed by the conditions that $y_i = 0$ if $y_i^* \leq 0$; $y_i = j$ if $\mu_{j-1} < y_i^* \leq \mu_j$, for $j = 1 \ldots J-1$; and $y_i = J$ if $y_i^* \geq \mu_{J-1}$, where μ_j is a parameter to be estimated (Greene, 2000).

A parallel lines regression model based on the cumulative distribution function of the observed ordinal scores is then estimated. It has the form:

$$g(\mathrm{Prob}(y_i \leq j \mid \mathbf{X}_i)) = \alpha_j + b\,\mathbf{X}_i\,, \quad 0 \leq j \leq J \qquad (2)$$

where α_j is the intercept parameter for the score level j. As the function g( ), we select the log-odds (logit) function. The model is estimated by maximum likelihood[vi].

4.2.1 The variables

The vector $\mathbf{X}_i$ of exogenous variables is selected to represent the structural and innovative characteristics of the firm. As a structural trait of the firm that may affect the degree of codification, we control for firm size. This is measured by the logarithm of the average number of employees of the firm in 1994 and 1996 (SIZE). The innovative investment of a firm is expressed by the intensity of R&D expenditure, measured by dividing expenditure on R&D by the total sales of the firm in 1996 (R&D). The CIS2 data set allows us to characterise the innovative process by means of variables that overcome problems related to the exclusive use of R&D statistics. Of these variables, we focus on four categories: (i) the innovative performance of the firm; (ii) the sources of knowledge relevant for innovation; (iii) the participation of the firm in innovation collaborations with different partners and (iv) the technological trajectories as expressed by the objectives of innovation of the firm.

Because each category has a large number of variables, many of which overlap with respect to the aspects of the innovation process, we reduce the number of them by means of principal components analysis, before the variables are used in the model estimation[vii]. For each category, the principal component analysis allows us to summarize most information contained in the variables into a few main factors, the latter uncorrelated between each other. In particular, we select the factors with eigenvalue not lower than one.

Looking into the results of the principal component analysis, the three variables of innovative performance – namely, the percentage of turnover based on products new to the market, new for the firm, and improved products – can be reduced to one factor. This factor accounts for 53 per cent of the total variance and is positively correlated to each of the original variables. We call this factor 'PRODINN' (See Appendix 1 Table I).

With regard to the sources of knowledge, the variables are measured on a four-point Likert scale for each of the ten different sources. These sources include: inside the firm (in-house), from the market (competitors; suppliers; customers; and consultancy agencies), from public and semi-public institutions (universities or other higher education institutes; government or private non-profit research institutes; and innovation centres funded by the government) and sources that are publicly available (conferences and journals; fairs and exhibitions). As a result of the principal components analysis, these variables lead to three main factors, which account as a whole for just above 55 per cent of the total variance (See Appendix 1, Table II). The first factor is positively correlated to all the other sources. It thus reflects the combined use of all sources and is labelled as 'embeddedness' factor (EMBED). This factor broadly captures the argument of Langlois (2001) that point to the role of 'institutions that

[vi] The procedure LOGISTIC of SAS/STAT is used.

embody knowledge' as a possible source of increasing returns through minimising the needs for transferring knowledge, codified or otherwise (p. 83). Similarly, this factor should capture some of the argument of David and Foray (1995) about the role played by the 'distributional power' of the system in fostering knowledge accumulation and growth.

The second factor is related positively to the contribution of suppliers and publicly available information (especially fairs and exhibitions) and negatively to the contribution of institutions outside the industry (universities, research institutes, innovation centres and consultancies). We name it the 'supplier-dominated' factor (SUPDOM). It contrasts a supplier-dominated system with a science-based system (Pavitt, 1984). The third factor reflects the distinctive use of in-house sources in combination with information from customers. We label it the 'in-house' factor (INHOUSE).

A group of dichotomic variables expresses the participation of a firm in innovation co-operation with different categories of partners: competitors, suppliers, customers, consultancy agencies, universities and innovation centres. The analysis of principal component leads to the extraction of a unique factor positively related to all the types of partnership, which accounts for about 49 per cent of the total variance (See Appendix 1, Table III). This reveals that those firms that participate in innovation co-operation do so in collaboration with many different types of partners, while other firms do not participate in co-operation at all. We label this the 'collaboration' factor (COLLAB).

[vii] The principal component analysis has been applied to reduce the number of variables from the CIS dataset in regression models, for example by Brouwer and Kleinknecht (1996); Klomp and Van Leeuwen (1999).

The last category of variables refers to the importance of different objectives of innovation, measured on a four-point Likert scale. Ten different objectives are described in the survey: exploiting new technological opportunities for the development of new or improved products; extending the products' range; opening up new markets or increasing market shares; reducing labour costs; reducing the costs of raw materials; reducing energy costs; improving the flexibility of production processes; fulfilling government requirements; and environmental concerns. This set can be summarised into three main factors, which account as a whole for 61 per cent of the total variability in the innovative strategies of a firm (See Appendix 1, Table IV). The first factor is positively related to all the considered objectives. It reflects the general exploration of a variety of objectives by the firm (ALLOBJ). The second factor is positively related to the objectives of extending the products' range and opening up new markets or increasing market shares, while it is negatively related to the objectives of reducing labour, materials and energy costs. Thus, it reflects the contrast between market-driven objectives and cost-saving objectives. We label it as the 'market' factor (MARKET). The third factor is related positively to the objectives of improving the flexibility of production processes and reducing labour costs; and negatively to the objectives of fulfilling government requirements and environmental concerns. It contrasts the importance of objectives related to the nature of the production process with objectives responding to external factors. We call this the 'production cost' factor (PRODCOST).

4.2.2 Econometric analysis

In the previous section, we showed that the intensity of use of codified sources of information varies across industrial sectors. In this section, we test whether the determinants of the use of codified knowledge vary across sectors. For this reason, we estimate the ordered Logit model for the codification score separately by industrial sector at the 2-digit SIC level[viii]. That is, we assume that in equation (2), the vector of coefficients b , expressing the effects of the size and innovative characteristics of a firm on the use of codified knowledge, may differ across sectors.

The estimation of the model at the firm level imposes a problem of selectivity of the sample. Of the 2205 innovative firms responding to the survey, 189 firms had to be rejected because of implausible data for the explanatory variables. Two criteria were applied in rejecting firms (Klomp and Van Leeuwen, 1999). First, firms were rejected if their employment data reported in the CIS-2 survey was not consistent with the figure reported in the Production Survey of Statistics Netherlands. Second, the ratio of total innovation expenditure to total sales was higher than 50 percent. Another 19 firms were rejected because their data on employment was missing from the Production surveys of 1994 and 1996. This produced a final sample of 1997 firms.

The estimation results for the model in 11 industries are presented in Table 5.
This shows that, overall, the size and innovative characteristics of a firm influence the use of codified knowledge. Across sectors a value of R-square between the minimum of 0.24 and the maximum of 0.47 is observed. In addition, the chi-square test based on the log likelihood statistic leads to the rejection in each sector of the hypothesis that the coefficients of the explanatory variables are, as a whole, equal to zero. However, the effects of the single variables may change across sectors. The only exception is represented by the factor of

[viii] Of the 2-digit level industries, the refined petroleum sector (SIC=23) has been excluded from the estimation because of the limited number of firms in the sector. We have also removed “other manufacturing” given the heterogeneity of its composition.

embeddeness (EMBED). This is the variable that is most significant. Its coefficient is statistically significant and with a positive sign in each sector. That is, the combined use of other sources of knowledge increases the probability of a firm relying more extensively on codified sources of knowledge.

Insert Table 5

Other variables that are fairly significant across sectors, and with a uniform sign when significant, are the size of the firm (SIZE), the R&D expenditure (R&D), the supplier-dominated factor (SUPDOM) and the all objectives factor (ALLOBJ). Firm size has a statistically significant and positive effect on the use of codified sources in four of the eleven industries (that is, in chemicals, rubber and plastics, machinery, and electrical/electronics equipment). The limited relationship between firm size and the use of codified sources suggests that the use of codified sources had more to do with firm strategies for using information for innovation than being a direct product of the size of the organisation. It suggests that proxy measures of codification can help to explain differences between firms in the nature of their innovation strategies.

R&D expenditure exerts a statistically significant and positive effect on codification in three low-tech industries, including paper, fabricated metal products and machinery and equipment. In these industries, firms that invest more in R&D also make more intensive use of codified sources. In all other industries, there is no direct relationship between R&D and the use of codified sources except in low-technology industries. This finding contrasts with the sectoral analysis that showed a strong link between levels of codification and R&D

expenditure at an industry level. The differences between firm-level and sectoral analysis suggest the benefits of adopting a dual empirical approach, including both firm-level and sectoral analysis, to exploring the link between codification and innovation.

The negative coefficient of the supplier-dominated factor (SUPDOM) is significant in three industries (food products, paper and transportation equipment). Within these sectors, firms that are science-based use more intensively codified knowledge than supplier-dominated sectors.

Finally, the coefficient of the all-objectives factor was significant in three sectors (food products, fabricated metal products and machinery). This shows that firms pursuing a combination of different objectives rely more on codified knowledge than firms with a focused strategy for innovation.

Another set of variables displays statistically significant effects of a different sign. For example, while firms in the textile industry that rely on in-house sources (INHOUSE) make more intense use of codified knowledge, the opposite is true in the machinery industry. The machinery sector presents something of an anomaly. In the machinery sector, there are strong differences between firms in innovative strategies. For those firms which rely on codified sources in the machinery industry, we found a strong positive relationship with R&D expenditure, size and collaborative arrangements. At the same time, we found a negative relationship between the use of codified sources and the use of in-house sources of innovation. This reflects the outward character of R&D intensive firms that rely on codified sources in this sector as compared to firms not using codified sources as intensively.

Collaboration was negatively associated with codification in both textiles and paper industries, indicating that firms which collaborate in these sectors do not widely use codified sources of information for innovation. Only in the machinery industry is there a positive relationship between collaboration and codification. In all other sectors, there is no relationship between collaboration and the use of codified sources. This finding suggests that attempts to influence patterns of co-operation between firms through investments in codified sources could have a limited impact on firms' innovative strategies.

In the paper industry, the use of codified knowledge is associated with innovation strategies aimed at cost saving (the coefficient of the MARKET factor is negative). Yet, in the transportation equipment industry, it is associated with market-driven strategies (the coefficient is positive). In the electrical/electronics industry, the use of codified knowledge is associated with production costs objectives (the coefficient of PRODCOST is positive); in the food and basic metals industries, it is associated with externally driven objectives (the coefficient is negative).

Finally, the variable that is least significant is the product innovation factor (PROINN). This is statistically significant, with a positive effect on the use of codified knowledge only in the publishing and printing sector and electrical equipment sector. This suggests that there is no direct relationship between the use of codified sources and innovative performance (as represented by product innovation here).

In short, embeddedness is the most significant effect and it increases the use of codified sources of information for innovation. Firm size, R&D investment, science-based system of innovation and wide-ranging strategies are significant in a number of sectors and tend to increase the use of codified knowledge. Conversely, the combination of use of codified knowledge and different typologies of innovation strategies, in terms of co-operation and technological trajectories, is sector- (and technology-) specific.

5. Conclusions

This paper has provided an empirical exploration of the relationship between codified knowledge and innovative performance. Using a proxy measure of codification, we have attempted to ground recent debates about codification of knowledge in an empirical framework. We have used this empirical framework to explore David and Foray's suggestion that codification offered the possibility of increasing the distribution power of the innovation system.

A key part of this argument was that codified sources of information for innovation were becoming increasingly important for innovation. We have attempted to show that among the sources of information for innovation, the codified sources are seen by firms to be relatively unimportant as sources of innovation. This data is only for one time period and future innovation surveys will provide more information about shifts over time in the importance of these sources for innovation. However, the current evidence suggests that David and Foray may have been somewhat too optimistic in ascribing a key role to these forms of information in the innovation process.

Using our proxy measure of codification, we have also shown that there are significant inter-industry differences in the extent to which firms rely on codified sources of information for innovation. The data shows that few industries rely heavily on codified sources of information for innovation. The use of codified sources may be sector-specific, limited in its impact to science-based sectors, such as pharmaceuticals. Our findings strongly suggest that absorptive capacity influences the extent to which firms can assess codified knowledge (Cohen and Levinthal, 1990).

In their paper, David and Foray suggested that it was important to focus on the distribution power of the innovation system, highlighting the role of codified sources in shaping patterns of innovation. Using a firm-level regression, we have explored this relationship. The regression results demonstrate that the use of other sources of information for innovation plays a key role in explaining the use of codified sources by individual firms. We have called this link between the use of codified sources and other sources of information the 'embeddedness' effect. Codified sources complement and are complemented by the use of other sources. Our results suggest that David and Foray were correct in arguing that codified sources may play a role in increasing the distribution power of the innovation system, that is, increasing the use of different sources of information for innovation. This finding needs to be put in the context of our industry-based analysis that showed wide variation in the importance of codification across different sectors and the importance of R&D investments in explaining industry-level patterns of codification. However, the regressions are suggestive of a link between the use of codified sources by individual firms and an expansion of the distribution power of the innovation system.

David and Foray also suggested that there is a relationship between the distribution power of an innovation system and the firm and the overall level of innovativeness of industries and firms. The regression results, however, do not support a statistical link between codification and innovative performance. Only in the printing and publishing industry and to a lesser extent electrical and optical equipment, was it possible find a link between codification and innovation performance at the firm-level. In all other sectors, there was no significant relationship between codification and innovative performance. This finding places a limitation on the third element of David and Foray's approach - the link between codification and innovativeness.

There are several policy implications of our study. The findings suggest that attempts to improve the distribution power of the innovation system by supporting codification exercises, such as computer-information networks, will have a limited impact on overall rates of innovation. Few industries rely on patent disclosure and computer-based information networks to innovate. Yet, expanding the use of codified sources may increase the importance of other parts of the innovation system. The impact of these distributional efforts will have the greatest impact in sectors where there are pre-existing investments in R&D and R&D personnel. Moreover, since most industries are not R&D intensive, nor are likely to become so in the short or medium term, the number of sectors where codified sources will be important will be modest and will therefore almost certainly have little overall impact on industrial innovation.

Further research is required on the relationship between codification and innovation. In this paper, we have explored the link between codification and innovative performance in an indirect way. Developing this link would involve considerable more econometric analysis than we have performed here. Future research should attempt to explore the extent to which codified sources of information for innovation are important across different countries. Comparison could be made at the level of individual sectors and between innovation firms across different European countries. It would also be useful to follow changes in these relations over time to determine whether codified sources of knowledge have become more important for innovation. With new data from the CIS 3, it might be possible to explore these relationships in a more dynamic framework.

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Table 1. Sources of information for innovation among innovative firms in different European countries, 1994-1996

(% of innovative firms scoring each source as "very important" on the Community Innovation Survey)[1]

Sources of information for innovation	United Kingdom	Belgium	Germany	Spain	France	Ireland	Netherlands	Austria	Finland	Sweden	Norway	Average
Sources within the enterprise	43	44	57	73	48	56	42	34	40	56	51	51
Clients or customers	54	55	45	53	32	58	14	57	44	69	54	46
Other enterprises within the enterprise group	19	23	39	n/a	24	46	14	22	18	17	27	26
Fairs and exhibitions	15	19	29	26	10	29	8	31	11	16	16	21
Suppliers of equipment	23	15	22	14	18	24	7	7	13	11	27	19
Competitors	17	24	22	22	9	29	5	17	8	17	19	18
Professional conferences	5	6	11	8	4	14	5	12	1	4	8	8
Universities	4	7	7	3	3	5	1	5	7	5	5	5
Consultancy	2	3	5	7	1	9	1	1	3	2	5	4
Computer-based information networks	3	3	5	n/a	4	8	1	5	3	2	4	4
Government or not-for-profit institutes	2	5	3	5	2	7	2	1	5	n/a	6	3
Patent disclosures	4	2	4	3	2	7	2	2	1	3	1	3

Note 1: Respondents were asked to rate the importance of the different sources of information for innovation on a four point likert scale.

Source: OECD Science, Technology and Industry Scoreboard, 1999, Benchmarking
Knowledge-based Economies

Table 2. Sources of information for innovative firms in the Netherlands, 1994-1996

(Number of firms using sources are expressed as percentage of firms with innovative activities)

	All Manufacturing Firms
Within the industry	*97*
Within the enterprise	91
Other firms within the enterprise (1)	66
Clients or customers	73
Suppliers	68
Competitors	63
External advisors	*54*
Consultancy enterprise	31
Research institutes (e.g. TNO)	32
Universities	22
Innovation centres (2)	25
Publicly available sources	*80*
Patent disclosures	18
Computer based information networks	20
Conferences, journals	69
Fairs and exhibitions	72

Notes

(1) The source of information is not relevant for independent firms

(2) Innovation centres are a typical Dutch phenomena. The main goal of innovation centres is to stimulate diffusion of knowledge in small and medium-size enterprises (SME's), especially to enhance the ability of SME's to enforce technological innovations. Innovation centres receive

Source: Klomp L., and G. Van Leeuwen, 1999, The Importance of innovation for firm performance, LNM-series 9902, Statistics Netherlands

Table 3. Codification score by industry, R&D intensity and percentage of codified users by industrial sector

	Average codication score[1]	Percentage of codified users	R&D intensity
Chemicals (including pharmaceuticals)	1.27	60%	4.04
Machinery and equipment	0.89	48%	2.24
Electrical and optical equipment	0.85	49%	3.71
Rubber and plastic products	0.72	43%	1.60
Paper and pulp	0.66	42%	0.53
Basic metals	0.66	48%	0.74
Transportation equipment	0.61	34%	4.36
Food	0.58	37%	3.19
Publishing and printing	0.50	36%	0.32
Fabricated metal products	0.48	36%	0.84
Textiles and leather	0.48	37%	0.91
Other manufacturing	0.32	31%	0.86

Note: Average codification score refers to combined score for each firm on the importance of patent disclosure and computer-based information networks as sources of information for innovation for each industry.

Table 4. Correlation matrix, Codification, R&D and Innovation Expenditure (n=62)

		Average codification score	R&D expenditure on sales	Percentage of R&D personnel	Innovation expenditure on sales
Average codification score	Pearson Correlation	1.000	.343**	.458**	.185
	Sig. (2-tailed)	.	.006	.000	.150
	N	62	62	62	62
R&D expenditure on sales	Pearson Correlation	.343**	1.000	.948**	.256*
	Sig. (2-tailed)	.006	.	.000	.045
	N	62	62	62	62
Percentage of R&D personnel	Pearson Correlation	.458**	.948**	1.000	.235
	Sig. (2-tailed)	.000	.000	.	.066
	N	62	62	62	62
Innovation expenditure on sales	Pearson Correlation	.185	.256*	.235	1.000
	Sig. (2-tailed)	.150	.045	.066	.
	N	62	62	62	62

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 5. Ordered Logit Regression Method, Determients of Codification

	Food products	Textiles and leather	Paper	Publishing and printing	Chemicals (including pharmaceuticals)	Rubber and plastic products	Basic metals	Fabricated metal products	Machinery and equipment	Electrical and optical equipment
SIZE	0.128	0.233	0.014	0.034	**0.382*** **	**0.292** **	-0.299	0.127	**0.201*** **	**0.357*** **
	(0.213)	(0.171)	(0.944)	(0.772)	**(0.000)**	**(0.014)**	(0.205)	(0.179)	**(0.006)**	**(0.000)**
RDFACTOR	0.119	-0.008	**0.382*** **	0.004	0.034	-0.013	0.227	**0.213*** **	**0.136** **	0.106
	(0.148)	(0.953)	**(0.005)**	(0.967)	(0.736)	(0.911)	(0.354)	**(0.009)**	**(0.035)**	(0.251)
PROINN	-0.029	0.012	0.222	**0.119***	0.005	-0.018	0.252	0.070	-0.064	**0.172***
	(0.739)	(0.930)	(0.157)	**(0.060)**	(0.955)	(0.875)	(0.251)	(0.416)	(0.373)	**(0.050)**
EMBED	**0.794*** **	**1.099*** **	**0.646*** **	**0.571*** **	**0.346*** **	**0.491*** **	**0.867** **	**0.390*** **	**0.497*** **	**0.775*** **
	(0.000)	**(0.000)**	**(0.003)**	**(0.000)**	**(0.002)**	**(0.000)**	**(0.045)**	**(0.000)**	**(0.000)**	**(0.000)**
INNSYS	**-0.347*** **	-0.044	**-0.568*** **	-0.117	-0.132	0.003	0.399	0.050	0.012	0.086
	(0.000)	(0.779)	**(0.001)**	(0.266)	(0.166)	(0.980)	(0.124)	(0.557)	(0.851)	(0.369)
INHOUSE	0.002	**0.304***	-0.304	-0.023	0.052	-0.047	0.091	-0.082	**-0.136***	0.065
	(0.986)	**(0.059)**	(0.117)	(0.837)	(0.613)	(0.682)	(0.744)	(0.398)	**(0.066)**	(0.536)
COLLAB	-0.028	**-0.285***	**-0.311***	0.088	0.151	0.162	0.120	-0.109	**0.109***	0.085
	(0.749)	**(0.098)**	**(0.081)**	(0.364)	(0.153)	(0.119)	(0.651)	(0.207)	**(0.092)**	(0.362)
ALLOBJ	**0.210***	0.041	0.215	0.017	0.026	-0.099	0.144	**0.345*** **	**0.188** **	-0.049
	(0.070)	(0.836)	(0.330)	(0.888)	(0.808)	(0.447)	(0.581)	**(0.001)**	**(0.014)**	(0.645)
MARKET	0.112	-0.258	**-0.294***	0.137	-0.042	0.009	0.160	0.145	0.008	0.137
	(0.299)	(0.110)	**(0.092)**	(0.263)	(0.667)	(0.938)	(0.547)	(0.151)	(0.912)	(0.182)
PRODCOST	**-0.202***	0.057	-0.218	-0.012	-0.106	0.057	**-1.056** **	-0.021	-0.024	**0.201** **
	(0.053)	(0.691)	(0.208)	(0.916)	(0.292)	(0.603)	**(0.010)**	(0.810)	(0.110)	**(0.032)**
R^2	0.40	0.40	0.35	0.24	0.30	0.27	0.48	0.27	0.32	0.47
N	247	108	79	154	143	127	39	227	295	196

Appendix 1.

Table I. Factor matrix of innovative intensity

	Factor 1
Turnover due to product new for the firm (% of total)	**0.688**
Turnover due to improved products (% of total)	**0.662**
Turnover due to products new for the market (% of total)	**0.823**
Cumulative explained variance (%)	53.0

Note: Extrated factors with eigenvalue higher than 1

Table II. Factor matrix of knowledge sources

	Factor 1	Factor 2	Factor 3
In-house sources	0.395	0.067	**0.633**
Clients or customers	**0.527**	0.244	**0.504**
Suppliers	**0.424**	**0.422**	-0.215
Competitors	**0.611**	0.250	0.268
Consultancy enterprises	**0.520**	-0.340	-0.097
Research institutes	**0.604**	**-0.530**	-0.060
Universities	**0.593**	**-0.493**	0.009
Innovation centres	**0.535**	-0.353	-0.117
Conferences, journals	**0.678**	0.322	-0.349
Fairs and exhibitions	**0.658**	**0.414**	-0.316
Cumulative explained variance (%)	31.5	45.0	55.2

Note: Extrated factors with eigenvalue higher than 1

Table III. Factors matrix of innovation co-operation with different kinds of partners

	Factor 1
Clients or customers	**0.676**
Suppliers	**0.705**
Competitors	**0.602**
Consultancy enterprises	**0.621**
Research institutes	**0.793**
Universities	**0.770**
Cumulative explained variance (%)	48.7

Note: Extrated factors with eigenvalue higher than 1

Table IV. Factor matrix of innovation objectives

	Factor 1	Factor 2	Factor 3
New products	0.378	**0.465**	0.041
Product quality	**0.526**	0.189	0.219
Product range	0.354	**0.735**	-0.020
New markets and market shares	**0.410**	**0.651**	0.015
Production process flexibility	**0.613**	-0.092	**0.523**
Reducing labour costs	**0.639**	-0.347	**0.469**
Reducing materials costs	**0.741**	-0.201	0.120
Reducing energy costs	**0.721**	-0.324	-0.248
Government requirements	**0.673**	-0.025	**-0.454**
Environmental damage	**0.710**	-0.175	**-0.500**
Cumulative explained variance (%)	35.2	50.4	61.2

Note: Extrated factors with eigenvalue higher than 1