Innovation as a latent variable: 
an alternative measurement approach

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Abstract: In searching for improvements in the measurement of innovation, in this paper we suggest the idea of conceiving innovation as a latent variable or concept, i.e., one that cannot be accurately defined or directly measured. We propose the use of multivariate statistical analysis (a combination of cluster and discriminant analysis) as a possible way to develop indirect measures of innovation that are more appropriate to the intrinsically imprecise nature of the concept to be measured. In this way, the problem of using an ambiguous and subjective ‘innovation definition’ is limited, reducing measurement errors. We obtain an ‘innovation intensity index,’ which is a weighted average of ten different predictors.

Keywords: measurement; innovation; multivariate; discriminant analysis; cluster analysis; latent variable, innovation index

JEL Classification: O32

1 Introduction

Since Schumpeter (1934, 1939), the conceptualizing of innovation has gone through a significant process of enlargement, successively including innovations of decreasing individual importance or less precision (incremental, service, organizational, marketing), and increasing diffusion. Once one recognizes that innovation is wider than R&D, one enters into an increasingly fuzzy world.

However, although the concept has evolved, the corresponding indicators have stayed the same (innovation expenditures, patent count, percentage of innovative sales, etc.). The result is that the available measurement instruments are inadequate, particularly in the case of services, because one cannot directly measure something that is intrinsically imprecise. In spite of this imprecision, researchers (Mairesse and Mohnen, 2003; Sirilli, and Evangelista, 1998; Smith, 2005) have been trying to measure innovation directly as if it were a clear, objective entity. The need for new measurement tools, better able to capture innovation, has long been widely acknowledged; nevertheless, no concrete proposals have been put forward thus far.

Consequently, out of a growing concern about the ability of available measures to assess innovation, this paper addresses the following research question: “Given the shortcomings of existing measures of innovation, are there strategies that can be devised to improve the measurement of innovation?”

The essay is structured in the following way: after a literature review on innovation measurement in Section 2, Section 3 suggests an alternative approach to innovation measurement. Section 4 presents the methodology applied in this research; the results obtained are discussed in Section 5. Finally, Section 6 summarizes the conclusions. Appendix A presents the text of the questionnaire.
2 Literature review

In the final report to the European Commission (Commission of the European Communities, 2007) an expert group on innovation recognizes that innovation, particularly in the service sector, remains difficult to study and measure. The report recommends that "more effort needs to be undertaken by the research community in developing new, but more robust, indicators that can actually better measure what innovation is about, rather than simply trying to adapt old modes of thinking in relation to innovation" (p. 15).

The issue of measurement in manufacturing industries has long been mainly dealt with by using ‘patents’ and ‘R&D expenditures’ as the basic indicators. Although these measures are relatively easy to obtain, they are not free of shortcomings. However, the most significant problem results from recognizing that innovation is larger than R&D. As far back as the 1980s, Cohen and Levin (1989, p. 1065), among others (Rosenberg, 1976; Kamien and Schwartz, 1982), recognize that “considerable effort is devoted to technological innovation outside a firm's formal R&D operation”. Consequently, these measures capture only a part of the phenomenon of innovation. The solution to this problem has been simply to enlarge the scope of the concept being measured from just R&D to ‘innovation’.

The first edition of the Oslo Manual (OECD, 1992) is the institutional expression of the widely accepted recognition that this use of R&D is too restrictive. As a consequence, the basic indicators became ‘innovation expenditure’ and ‘whether or not the firm has innovated’ and later ‘share of innovative sales’ (Mairesse and Mohnen, 2001, 2002). To obtain these indicators, the solution to the measurement problem adopted by OECD, since the first R&D statistical Frascati Manual (OECD, 1963), “has been to write definitions (…) [and] this approach to measurement has been taken with innovation surveys” (Smith, 2005, p.151). Furthermore, successive editions of the Oslo Manual have enlarged the definition of innovation, first to include services, in the 2nd edition of 1997, and then to include non-technical innovations (organizational and marketing innovations) in the 3rd edition of 2005. The present definition of innovation, in this last revision, is the following:

“An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method or a new organizational method in business practices, workplace organization or external relations. (…) The minimum requirement for an innovation is that it must be new (or significantly improved) to the firm.” (Oslo Manual, OECD 2005, p. 46)

Such an approach is obviously useful and has led to a very rich stream of research. However, a group of authors (Preissl, 2000; Smith, 2005; Tether and Hipp; 2002) acknowledge the difficulties encountered in measuring innovation, related mainly to the degree of newness implied by an innovation and the ability of firms to provide accurate data.

Bilderbeek et al. (1998, p. 11) point out that “as usual in the study of innovation, there are thorny problems concerning when a product, function or concept is really new”. In addition, Tether and Hipp (2002, p. 173) acknowledge that “in practice, determining whether expenditure does or does not relate to innovation can be problematic and it can be difficult to obtain accurate information from firms” (assuming the problem lies in the lack of ability of firms to give this information). Hipp et al. (2000) point out that because the type of questions based on the Oslo Manual ask firms about their innovative activities from a subjective perspective, the answers depend on the respondents’ understanding of what does and does not constitute innovation. These
difficulties are reflected in the researchers’ finding that significant disagreement exists in the classification of innovations, using data from a large-scale survey conducted in Germany.

The same difficulties are reported by Preissl (2000). This researcher considers that the origin of the problem lies in a “deficit in communication between researchers and firms”. This deficit stems from the fact that “managers, particularly in service firms, are often not familiar with the term innovation” and the procedure usually used to avoid the problem (offering explanations and/or definitions or using more general terms like ‘changes in the firm’ or ‘new services’) is not effective.

Again, Tether (2005) recognizes that “innovation implies more than just change” and hence there is the issue of “the extent of change implicit in the term innovation” (p. 182). Smith (2005, p.149) also recognizes that “a fundamental definition issue is what we actually mean by ‘new’”. Godinho (2007) notices that in CIS surveys, “it has been perceptible that the concepts of innovation with which respondents have been confronted are susceptible [to] different interpretations, according to the context and the moment of the response.”

More recently, Beck (2008) reports on the efforts of a British organization to create a new innovation index and identifies as a subject to be dealt with the question of “how to define innovation,” considering that “innovation today is multidirectional, not only about producing new products but also about services, business models and processes” (p.1).

All these authors just acknowledge these problems but do not elucidate possible solutions.

Tether and Howells (2007) go a step further, beyond pointing to measurement difficulties and “develop an experimental approach to explore the multiple dimensions of change in business” (p.37). In practice, it consists of asking firms about eight ‘dimensions of change’ including what might be considered traditional, technological aspects of innovation and also covering soft and organizational aspects. A frequencies analysis is then conducted on the resulting data.

A large number of innovation indexes (scoreboards and scorecards) produced by consulting firms and government agencies, among others, are constructed using collections of questions subsequently scored and added to obtain a synthesis number. One of the best-known measures of this type is the European Innovation Scoreboard, now in its eighth edition. This last edition (European Commission, 2009) puts a stronger focus on services and non-technological aspects but is still calculated by taking the un-weighted average of the normalized values of 29 individual indicators (Hollanders and Cruysen, 2008).

Most of these indexes apply only to countries and not to firms; but, above all, the most significant drawback is that they are just averages of individual indicators, chosen on a strictly subjective basis and with no differentiation among them in terms of relative importance. Even if weights are included, these are also subjectively chosen. As a result, although they are synthesis measures, they are no more robust than other indicators.

Finally, Mohnen and Dagenais (2000) propose a less subjective approach based on the econometric prediction of the conditional expectation of innovation from an estimated explanatory model. Although by far more objective and reliable than the previously mentioned indexes, it applies only to groups of firms (sector, country) and not to individual firms.

The current critics, most of them having in mind service sectors (quite recently, Tether and Howells (2007, p.52) admitted that “innovation in services provides a challenge for the measurement of innovation”), point to the limited capability of available measures to capture the full range of innovation dimensions. However, they have been unable, until now, to propose new indicators more adequate to the object being measured. This short literature review reveals that no
substantially new measurement approach has been proposed so far, except the econometric approach of Mohnen and Dagenais (2000), which does not apply to the level of the individual firm. Although providing more insights into the innovation process, these attempts simply add new questions put forward on a merely subjective basis.

3 An alternative approach

From the literature review in the previous section, it is possible to perceive that the fundamental approach to innovation measurement, taken so far, is based on the implicit assumption that an ‘objective’, operational ‘innovation definition’ is possible. Asking for turnover due to innovations, or any other currently used indicator, implies that previously one has already determined what an innovation is and that innovations are identified (at least very roughly).

This undisputed implicit assumption has, in fact, conditioned the search for innovation measurements and indicators; this search seems to have reached a dead end. But if we drop that assumption, new possibilities become available. In particular, we suggest recognizing that ‘innovation’ is impossible to define with rigor and objectivity. Hence we can consider it a ‘latent variable’, a statistical concept used for a long time in social and behavioral sciences (for concepts such as ‘personality’, ‘intelligence’ or ‘social class’). A ‘latent variable’ is a variable that cannot be measured directly. As a result, in order to obtain information on such variables, one is forced to consider other variables that can be observed (i.e., ‘manifest variables’) and that are related to the latent quantities of interest, but which may contain additional noise or error. In this way, ‘latent variables’ can be included in statistical models.

Considering this new characterization, several multivariate statistical techniques, founded on the idea of a ‘latent variable’ (in particular Factor, Cluster and Discriminant Analysis) become available and adequate to innovation measurement. This type of analysis has been successfully used in many fields but has not been explored, as far as we know, in the area of innovation.

We would like to stress that the approach to measurement we are suggesting clearly departs from the conception of innovation as an isolated event (which can be identified individually) and, instead, follows a perspective of innovation as a process (which cannot be perfectly isolated but only assessed through indirect indicators).

4 Methodology

Given our exploratory purpose, the research design required the acquisition of new primary data. Moreover, a sufficient number of observations was required to allow the emergence of underlying patterns. To attain these objectives, the direct face-to-face, semi-structured, interview method (with top managers) was chosen to collect the data.

Given the scope limitations imposed by this method, only one activity sector was included in the sample. The IT Services sector was chosen for two reasons. First, it is a services industry where the measurement problems are more acute. Second, it is characterized by rapid technological development and changing market demands. Because this research was mainly exploratory, it seemed useful to begin with a sector where the phenomena of interest (innovations) are frequently occurring and readily transparent.

In order to reduce the influence of structural factors due to the country of origin, it was considered essential to conduct the interviews in at least two countries. Denmark and Portugal were chosen because their respective economies have several structural similarities but, at the same time, have deep differences, for instance at the cultural level, which makes them interesting choices.
The questionnaire (see Appendix A) has eleven sections: General Information, Markets, Supply, Innovation Process, Innovation Output, Innovation Input, Innovation Impact/Effects, Conditioning Factors of Innovation, Management Characteristics, Human Resources and Networking, adding up to 258 variables. The interview material was collected from 62 firms (31 in each country). Only in four firms was the CEO not the interviewee.

The data gathered (in Denmark between August 10th 2005 and September 17th 2005 and in Portugal between June 7th 2006 and August 25th 2006) were analyzed using multivariate statistical methods, in particular discriminant and cluster analysis. Discriminant analysis allows us to detect latent subjacent variables, which cannot be measured directly, through a set of indicators (the predictors). In this way, it may be possible to build a new indirect indicator because several variables, which we can observe directly, have a subjacent common concept, in this case, innovation intensity.

This methodology requires that a known classification of firms must be available. We could create this classification subjectively, using the researcher experience obtained during the interviews. However, the problem is complex and the risk of incorrect classifications seems severe, pointing to the need of a less subjective procedure for classifying firms. Therefore we searched for a more objective methodology and a cluster analysis was performed for this purpose.

5 Results

First, through the cluster analysis we were able to identify two ‘natural’ groups related to innovation intensity, one that might be labeled ‘more innovative’ firms and the other labeled ‘less innovative’ firms. These clusters clearly correspond to two different intensities of innovative behavior.

Second, the discriminant analysis conducted over these clusters produced a discriminant score that has a substantive interpretation: it may be interpreted as a true ‘innovation intensity indicator.’ This index is a weighted average of ten different variables or predictors (number of client countries, competitive position, innovation intensity, relative innovation, competitive advantage, innovation importance, export to developed countries, innovation trigger factors group, increase differentiation, and market scope). The validity tests conducted allow us to conclude that we have a valid discriminant model. Consequently, it is a useful tool for classifying new firms in terms of innovation intensity.

Cluster analysis

In the first step of our research, we seek to identify the ‘natural’ groups, or clusters, of firms based on a multivariate profile, if it exists, which both minimizes the within-group variation and maximizes the between-group variation. These clusters will be subsequently used in the discriminant analysis.

We use the Log-likelihood distance measure to determine how the similarity between clusters is computed because categorical variables are used. On the other hand, the Two-step cluster analysis algorithm was chosen for cluster membership assignment because it can be applied to categorical variables as well as to continuous variables, to which the more traditional clustering techniques, like the hierarchical or the K-means procedures, are restricted. This procedure also determines automatically the optimal number of clusters based on either the Bayesian Information Criterion (BIC) or the Akaike Information Criterion (AIC).

The variables chosen for the cluster analysis determine which features control the grouping. We started from a workable set of 72 variables, with 62 observations, excluding from the 258 initial variables all qualitative variables as well as variables with missing values. Next,
we followed a reduction strategy, starting with this set of variables and iteratively reducing it. The elimination process followed the chi-square statistic criterion, tracking a single variable across all clusters.\textsuperscript{1}

Along this exploration process, a clear pattern emerged. Not surprisingly, it involved innovation variables (innovation intensity, relative innovation, innovation importance and trigger factors), creativity variables (creativity importance and existence of creativity incentives) and market variables (competitive position, market scope, number of export countries, number of subsidiaries and development level of export target countries). This set of twelve variables was explored in greater detail in search of a solution with more homogeneous and clearly defined clusters. We arrived at a solution with six variables: \textsuperscript{2}

- Innovation Trigger Factors Group
- Export to Developed Countries
- Market Scope
- Innovation Importance
- Innovation Intensity
- Competitive Position

The optimal number of clusters was automatically selected by the two-step clustering algorithm, based on the Schwarz Bayesian Criterion (abbreviated BIC).\textsuperscript{3} The cluster solution yielded two clusters, quite different in size. The first cluster is the larger, containing 72.6\% of firms (N=45), and the second cluster accounts for only 27.4\% of firms (N=17).

In order to interpret the clusters obtained and identify the associated firm profiles, we examined the composition of the clusters by analyzing the distribution of each of the six variables across clusters. The structure that emerged from the sample corresponds, in general, to the segmentation of firms that was expected: two groups of relatively ‘homogeneous’ firms, one that might be labeled ‘more innovative’ firms (the larger cluster) and the other labeled ‘less innovative’ firms.

On one hand, ‘more innovative’ firms have a larger market scope and export mostly to developed countries. They tend to display a proactive behavior towards innovation (relying on internal innovation trigger factors), to consider innovation very important and to claim to perform innovation on a continuous basis. Most of them see themselves as being ahead of or at the same level as their most significant competitors.

On the other hand, ‘less innovative’ firms are characterized by having a more reduced market scope, essentially national and local; almost none exports to developed countries. They tend to display a reactive behavior towards innovation (relying on external innovation trigger factors), to consider innovation not so important and to claim to perform innovation not so intensively. They perceive themselves as being ahead or behind their most significant competitors, but not at same level.

\textsuperscript{1} The two-step clustering algorithm automatically standardizes all the variables, so that they all contribute equally to the distance or similarity between the cases, independently of their scale of measurement.

\textsuperscript{2} The inverse approach to variable selection was also performed, starting with one variable (innovation intensity or innovation importance) and successively adding different variables. However, no significantly different results were achieved.

\textsuperscript{3} The Akaike Information Criterion (AIC) was also experimented but no significant differences were observed.
Discriminant analysis

We are interested in distinguishing between firms with different innovative propensities and for that we need to find characteristics (indirect indicators) that allow us to classify firms as more or less innovative. Thus, the purpose is to determine if we have variables (predictors) that allow us to discriminate between firms that have different innovative intensities, in other words, to predict or measure innovation intensity.

For this analysis, as we have already seen, known groups of firms must be available, and we used the two firm groups generated in the cluster solution presented previously, which we called ‘more innovative’ firms and ‘less innovative’ firms. We examined whether these two mutually exclusive groups of firms could be distinguished from each other based on a linear combination of values of predictor variables (indirect indicators).

Again, we started from a workable set of 72 variables, excluding from the 258 initial variables all qualitative variables as well as variables with missing values. After a large number of experiments with different number and combinations of variables, we found that 10 variables contribute significantly to evaluate innovation intensity. This set of variables is the one that produced the best results in terms of the overall quality of the discriminant function (eigenvalue and canonical correlation of the discriminant score) and of the correct-classification rate (an indicator of how well the model predicts the group to which a case belongs), while still capturing the differences between the groups.

Table 1 shows these variables (predictors) and the respective computed coefficients (reflecting the contribution of each individual predictor) in the discriminant function.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market scope</td>
<td>0.446</td>
</tr>
<tr>
<td># of exporting countries</td>
<td>0.003</td>
</tr>
<tr>
<td>Competitive position</td>
<td>-0.099^4</td>
</tr>
<tr>
<td>Innovation intensity</td>
<td>0.084</td>
</tr>
<tr>
<td>Relative innovation</td>
<td>-0.072</td>
</tr>
<tr>
<td>Innovation contribution to competitive advantage</td>
<td>0.272</td>
</tr>
<tr>
<td>Innovation importance</td>
<td>0.002</td>
</tr>
<tr>
<td>Export to developed countries</td>
<td>0.901</td>
</tr>
<tr>
<td>Innovation trigger factors group</td>
<td>0.362</td>
</tr>
<tr>
<td>Innovation contribution to increase differentiation</td>
<td>0.169</td>
</tr>
</tbody>
</table>

We verified that the discriminant function has a large efficacy; in other words, the discriminant model as whole fits the data quite well. In fact, the function eigenvalue is quite large (3.432), indicating that the function scores vary a lot between the groups and vary little within a group. The canonical correlation has also a very large value (0.880), indicating that almost 90% of the observed variability in the discriminant scores is explained by differences between groups (and not within groups).

^4 The variables ‘competitive position’ and ‘relative innovation’ have the scale of measurement in reverse order relative to the remaining variables (1ahead/much more instead of nothing/non-existent, 5behind/much less instead of very much/continuous).
Testing the equality of discriminant function means also confirms this result. The value of the Wilks' Lambda statistic is 0.226, which means that only a little more than 20% of the total variance in the discriminant scores is not explained by differences among the groups. This small value of the test statistic indicates that the function has a great discriminatory ability. We further observe that there is a large difference between the average values of the discriminant function for the two groups of firms, meaning that the discriminant function results in different scores for cases in different groups. All these results indicate, with a high probability, that the data constitute a sample from two separable populations, therefore also validating the results from the previous cluster analysis.

In terms of the discriminant model’s validation, the null hypothesis that the average discriminant scores in the population are the same in the two groups has been rejected and all the indicators point to a valid model. However, telling how well the discriminant function predicts the group to which a case belongs requires using the discriminant function to assign cases to a group. Table 2 shows the practical classification results of using the discriminant model to predict group membership.

**Table 2  Classification results**

<table>
<thead>
<tr>
<th>TwoStep Cluster Number</th>
<th>Predicted Group Membership</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Original</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>1</td>
<td>42</td>
</tr>
<tr>
<td>Count</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>%</td>
<td>1</td>
<td>93.3</td>
</tr>
<tr>
<td>%</td>
<td>2</td>
<td>11.8</td>
</tr>
<tr>
<td>Cross-validated(a)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Count</td>
<td>1</td>
<td>41</td>
</tr>
<tr>
<td>Count</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>%</td>
<td>1</td>
<td>91.1</td>
</tr>
<tr>
<td>%</td>
<td>2</td>
<td>11.8</td>
</tr>
</tbody>
</table>

Note: 91.9% of original grouped cases correctly classified. 90.3% of cross-validated grouped cases correctly classified. (a) Cross validation is done only for those cases in the analysis. In cross validation each case is classified by the functions derived from all cases other than that case.

We see that 91.9% of the 62 firms used in computing the discriminant scores are correctly classified using the discriminant function. This finding suggests that, overall, the model is in fact correct more than 9 out of 10 times.

However, classifications based upon the cases used to create the model tend to be overly optimistic in the sense that their classification rate is inflated. One way to attempt to correct this bias and obtain more accurate estimates of the true misclassification rate is the leave-one-out cross-validation, classifying each case while leaving it out from the model calculations. Table 2 shows that the cross-validation results are lower than the original results, but this reduction is very small (90.3% of firms correctly classified). However, this method is still generally optimistic. Nevertheless, the rate of cases correctly classified is so high that we are confident that an even more reliable and conservative estimate would be sufficient to validate and accept this discriminant model.

In short, we may conclude that we have a valid discriminant model able to distinguish ‘more innovative’ firms from ‘less innovative’ firms. Consequently, the discriminant score has a substantive interpretation: it is an innovation intensity index (a weighted average where the
weights are the discriminant function coefficients). This index is a continuous variable that can be further introduced in econometric analysis as an innovation indicator:

\[
\text{Discriminant Score} = 0.446 \times \text{market scope} \\
+ 0.003 \times \text{number of client countries} \\
- 0.099 \times \text{competitive position} \\
+ 0.084 \times \text{innovation intensity} \\
- 0.072 \times \text{relative innovation} \\
+ 0.272 \times \text{innovation contribution to competitive advantage} \\
+ 0.002 \times \text{innovation importance} \\
+ 0.901 \times \text{export to developed countries} \\
+ 0.362 \times \text{innovation trigger factors group} \\
+ 0.169 \times \text{innovation contribution to increased differentiation}
\]

A further experiment conducted using innovation variables exclusively (without any market related variable) produced less positive results. The rationale for performing this experiment was to check if it was possible to construct a discriminant score closer to a more ‘pure’ concept of an ‘innovation index’. Such a score proved to be a second best. Although the model met the basic criteria of the validity tests, it displayed a worse performance than the more ‘hybrid’ score (the one including market variables). In fact, this result is quite interesting and suggests an inextricable link between innovation and market. This connection makes perfect sense considering that, at the level of the firm (not the lab), innovation activities are pursued not because of innovations by themselves but because of their impact on firm performance in the market. Consequently, a firm more actively concerned about market considerations will tend to pursue innovation more intensively.

6 Conclusions

This study affirmatively answered our research question, “Given the shortcomings of existing measures of innovation, are there strategies that can be devised to improve innovation measurement?” In the line of thought of such authors as Bilderbeek et al. (1998), Hipp et al. (2000), Tether (2005), Smith (2005) and Godinho (2007), who identify a fundamental problem concerning the lack of objectivity in the concept of innovation, we suggest the idea of conceiving innovation as a latent variable or concept, i.e., one that cannot be fully defined or directly measured. Accepting this new perspective, not simply as a problem but as a fact that we have to address directly, allows us to propose the use of multivariate statistical analysis (a combination of cluster and discriminant analysis) as a possible way to develop indirect measures of innovation that are more appropriate to the inaccurate nature of the concept to be measured. In this way we go a step further than previous authors, who just acknowledge the problem. And, in contrast with other approaches (Tether and Howells, 2007) we propose a methodology that is not simply a variation of previous ones.

In addition, we give evidence of the possibility of constructing such an indirect innovation index, at the level of the firm, combining several variables, which can be observed and do not require the identification of individual innovations. In fact, the discriminant analysis produced a score that may be interpreted as a true ‘innovation intensity indicator’. This index is a weighted average of ten different variables that can be used to predict whether a given firm is ‘more innovative’ or ‘less innovative’. The validity tests that we conducted point to a very good rate of correct classifications. These findings seem quite relevant because they provide evidence for the possibility of constructing innovation indicators combining several variables, based on
statistical methods and not simply on subjective basis. Much more important than the application of the index type measure to firms instead of countries, this last characteristic is the most important aspect that distinguishes the measurement tool presented in this paper from other innovation indexes (Hollanders and Cruysen, 2008).

In this way, we may assess innovation in an indirect way, one less dependent on a single definition and more robust to measurement errors.

This result also points to the limits of assessing innovation with a single indicator, since its multidimensional nature is emphasized. We also found that market-related variables play a significant role in the construction of this innovation index, revealing that firms’ behavior towards market considerations is strongly and positively linked to attitudes and behavior towards innovation.

This approach contributes to the improved measurement of innovation because it leads to innovation indicators that are more objective, reliable and robust to measurement errors than existing measures due to the fact that they result from a statistical procedure and do not require identification of individual innovations. In this way, the proposed method eliminates the problem of having very different individual interpretations of an intrinsically ambiguous and subjective ‘innovation definition’. Globally, the results are very promising. They are also sensible, logical and coherent. This approach seems to us a relevant contribution, opening a path for the future development of new innovation measures.

In this empirical study we also constructed a new, very rich and reliable database (it was all collected and created by the researcher), with the results of 62 interviews with top managers of IT services firms, in Denmark and Portugal, on 258 variables.

The most important limitation of this research is that it is based on a single activity sector. Furthermore, the number of observations although significant, is not very large. Therefore, further investigation should be conducted with larger data sets. Future research should also test whether the same relations are observed in other industries, manufacturing and services, and comparisons should be made between different types of sectors. We will probably arrive at different scores for different industries. For some industries, this kind of measure may not even bring much improvement relative to existing indicators. Another immediate development of this work might be to apply this discriminant score to a set of known firms, in the same industry, to test the reliability of the obtained innovation index.

In fact, a great deal of research needs to be conducted on this approach until we arrive at a solid set of predictors and coefficients that can actually be used in applied work to measure innovation intensity of firms. This study is only a first step pointing to a new direction for the development of a completely different (as far as we know) type of innovation indicators.

If the ideas put forward in this paper are developed and lead to the results the research suggests as possible, virtually everyone studying innovation, including practitioners, will benefit because the indicators will be improved. Furthermore, the variables that make up the index point to strategic directions for firms to pursue in order to foster their innovative and market performance. Hence, this research may have immediate practical implications and may be directly useful for management’s strategic decisions.
7 References


**Acknowledgments**

My warmest thanks to all the interviewees (whom I cannot name for reasons of confidentiality) for the time and interest they devoted to this study despite being busy with their own work. I especially would like to thank Peter Lotz and Jens Christensen for receiving me so warmly at Copenhagen Business School, where I conducted the empirical part of the research in Denmark as a visiting researcher, and for their help and stimulating discussions. The author has benefited from financial support of GEFAGE-UE (FCT/MCES).
Appendix A

Private information
Firm Name:  
Web page:  
Interviewee:  Name:  E-mail:  Position:  

Identification Code:

A. General Information

A.1. Year of establishment, in Denmark/Portugal:

A.2. Location of headquarters in Denmark/Portugal:

A.3. Location of other offices, in Denmark/Portugal:

A.4. What factors determined the geographical location of the firm/offices

Vicinity of customers  \(4 = \text{very important} \quad 3 = \text{important} \quad 2 = \text{not much important} \quad 1 = \text{not at all important}\)

Growth prospects in the region
Vicinity of universities
Infrastructures
Other (specify)

A.5. Is the firm independent or part of a group?

A.5.1. If it is part of a group, where are located the headquarters?

B. Markets

B.1. How do you name the market in which you operate?

B.2. In terms of geographical scope, which is the relevant market for this firm? (Local, National, EU, Global)

B.3. International activities

B.3.1. Exports – to which countries?

B.3.2. Subsidiaries abroad – where?

B.3.3. Imports – from which countries?

B.3.4. Partnerships – with whom and from which country?

B.4. Who are your most important competitors?

B.4.1. How do you position yourself in relation to them? (ahead, equal, behind)

B.4.2. If you are not equal, what is the reason for your competitive advantage/disadvantage?
C. **Supply**

C.1. What is the main line of business of the firm?

C.2. Are there other lines of business? (Y/N) Which ones?

C.3. Could you give a brief description of the Services portfolio?

C.4. What is the average time needed for the provision of your services?

C.5. Does the company sell any HW? (Y/N)
   C.5.1. If yes, what is the % of the turnover due to HW?

C.6. Does the company sell any packaged SW? (Y/N)
   C.6.1. If yes, what is the % of the turnover due to PSW?

4=Always/Very much  3=Very often/Much  2=Occasionally/Little  1=Never /Nothing

C.7. To what extent is the client involved in the services provision?

C.8. To what extent are producer-client relationships, permanent?

C.9. How important is client-specific business know-how?

C.10. What are the most important factors for tightening linkages with the client?

D. **Innovation Process**

D.1. In your firm, is innovation an activity
   Non existent (follow to E.8.)
   Non-intentional/ad-hoc
   Intentional but occasional
   Continuous

D.2. If it is a continuous activity, how is it organised?

D.3. Can you identify the trigger factors of the innovation process?

D.4. Can you describe the process of developing an innovation?

D.5. Could you attribute a measure of structure/formalization of the innovation process? (4=very high 3=high 2=low 1=very low)

D.6. Could you attribute a measure of technological complexity of the innovation process? (4=very high 3=high 2=low 1=very low)

D.7. Could you attribute a measure of management complexity of the innovation process? (4=very high 3=high 2=low 1=very low)
E. Innovation Output  *(you succeeded in introducing an innovation in the market)*

E.1. In relation to the other firms in your market, do you consider your firm

- Much more innovative
- More innovative
- Equally innovative
- Less innovative
- Much less innovative

E.2. Did your firm introduce any innovation, in the last three years? (Y/N)  *(if NO, follow to E.7.)*

E.3. Who did most of the innovations?

- The firm
- The firm with the group to which it belongs
- The firm in cooperation with others outside the group
- Others

E.4. What was the number of innovations, in each year?  

<table>
<thead>
<tr>
<th>Year</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td></td>
</tr>
<tr>
<td>2003</td>
<td></td>
</tr>
<tr>
<td>2002</td>
<td></td>
</tr>
</tbody>
</table>

E.5. Could you describe the more significant innovations?

E.6. Can you classify the innovations that were introduced by your firm, in the last three years, as:  
*(in each category, indicate frequency)*

<table>
<thead>
<tr>
<th>E.6.1.</th>
<th>Major innovation or Important or Minimal</th>
</tr>
</thead>
<tbody>
<tr>
<td>E.6.2.</td>
<td>Service/Product or Process</td>
</tr>
<tr>
<td>E.6.3.</td>
<td>Incremental or Radical</td>
</tr>
<tr>
<td>E.6.4.</td>
<td>New to the market or New to the firm</td>
</tr>
</tbody>
</table>

E.7. Were there any abandoned innovation projects, in the last three years? (Y/N)

- If YES indicate:
  E.7.1. How many?
  E.7.2. What were the reasons for the abandonment?

E.8. Did your firm implemented any new or significantly improved method in the following areas, in the last three years? (Y/N)  *(If YES describe briefly.)*

- E.8.1. Management
- E.8.2. Strategy
- E.8.3. Structure
- E.8.4. Marketing
- E.8.5. Other

E.9. What are the reasons for not innovating?
F. Innovation Input

F.1. In your firm, is R&D an activity

   Non existent
   Occasional
   Continuous

F.1.1. If it is a continuous activity, how is it organised?

F.2. How important are the following instruments for innovation protection:

   4=Very much   3=Much   2=Little   1=Nothing

   Patents
   Trademarks
   Copyright
   Secrecy
   Complexity
   Anticipation

G. Innovation Impact / Effects

G.1. Do you innovate because your previous innovation experience proved to pay-off? (Y/N)

G.2. Can you estimate the % of total turnover due to innovations, in each year?  2004  2003  2002

G.3. Do you have any means of quantifying the effects resulting from the introduction of individual innovations? (Y/N)

G.4. In what time horizon would you say that the financial results from innovation start to be obtained?

G.5. Did the innovations that your firm introduced had an effect on:
   4=High  3=Medium  2=Low  1=Irrelevant

   G.5.1. Improving production flexibility
   G.5.2. Improving production capacity
   G.5.3. Enlarging services portfolio
   G.5.4. Improving service quality
   G.5.5. Enter new markets
   G.5.6. Changing the number of employees (+ or -)
   G.5.7. Improving specialisation in the client’s industry
   G.5.8. Increasing market share
   G.5.9. Impact on competitive advantage (as a source of competitive advantage)
       G.5.9.1. Reducing costs
       G.5.9.2. Increasing differentiation
       G.5.9.3. Increasing the knowledge base of the firm
   G.5.10. Impact on customers
       G.5.10.1. If not irrelevant, can you describe this impact?
G.5.11. Improving relations with customers/partners:
G.5.11.1. Increase customer loyalty
G.5.11.2. Building trust and relationship enhancement
G.5.11.3. Other (identify)

G.5.12. Effects at the market level:
G.5.12.1. increasing concentration on the supply side
G.5.12.2. increasing competition

H. Conditioning Factors of Innovation

H.1. Favouring factors: What is the importance that you attribute to the following favouring factors of innovation

4=Very important  3=Important  2=Not much important  1=Nothing important
Government support
Vicinity of Universities
Increased competition
Institutional environment (specify)
Other (identify)

H.2. Obstacles: What is the importance that you attribute to the following obstacles to innovation

4=Very important  3=Important  2=Not much important  1=Nothing important
Economic risk
Lack of financial resources
Lack of technological knowledge
Lack of market knowledge
Reduced size of the market
Institutional environment (specify)
Other (identify)

H.2.1. With what measures could the obstacles be alleviated?

H.2.2. Which actors and organisations should take the responsibility for doing it?

H.3. Do you see a role for public policy? (Y/N) If YES, which one?

H.4. Do you see a role for universities? (Y/N) If YES, which one?
I. Management Characteristics

I.1. Top management characteristics
I.1.1. What is the academic degree of the top manager?
I.1.2. Is it a family or professionally run firm?

I.2. Culture
I.2.1. What are the main values of the firm?
I.2.2. How important is knowledge sharing in the firm’s culture? (4=Very 3=Much 2=Little 1=Nothing)
I.2.3. How important is creativity in the firm’s culture? (4=Very 3=Much 2=Little 1=Nothing)

I.3. Business strategy: What is the main basis for competing?
I.3.1. Price (strategy 1) or differentiation (strategy 2)?
I.3.1.1. If it is differentiation, what are the main differentiating elements?
I.3.2. Specialised (niche; strategy 3) or general (strategy 4)?
I.3.2.1. If it is specialised, in what segments?
I.3.3. To what extent is innovation important in the strategy of the firm? (4=Very 3=Much 2=Little 1=Nothing)

I.4. Organisation
I.4.1. What is the type of the firm’s structure (simple, hierarchical, divisional, matrix, network)?
I.4.2. To what extent is the work organised on the basis of projects and teams? (4=Very 3=Much 2=Little 1=Nothing)

I.5. Human resources policy
I.5.1. Do you have incentives for creativity motivation? (Y/N)
I.5.1.1. If YES, which ones?
I.5.2. Do you have incentives for employees and executives retention? (Y/N)
I.5.2.1. If YES, which ones?
I.5.3. Do you have a written policy of knowledge management? (Y/N)
I.5.4. Do you have alliances or partnerships for knowledge acquisition? (Y/N)

J. Human Resources

J.1. Which are the key occupations in your business?
J.2. What are the most important qualifications/competences requirements?
J.3. Does the level of skills offered in the labour market correspond to your qualification requirements?
J.4. What are the most important needs for training?

K. Networking

K.1. Is networking among organisations common? (Y/N)
K.2. Did it become more common in recent years? (Y/N)
K.3. What is the importance of networking for the success of the company? (4=Very important 3=Important 2=Not much 1=Nothing)