INTANGIBLE INVESTMENT AND HUMAN RESOURCES

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Abstract

Statistical cluster techniques are applied in the development of two new taxonomies of manufacturing industries. The first focuses on the distinction between exogenous, location dependent comparative cost advantages, such as the relative abundance of capital or labour, and endogenously created firm specific advantages resulting from intangible investments in marketing or innovation. The second taxonomy discriminates between industries according to their employment of skilled labour. Finally, econometric tests are used to investigate the presumed complementarity between intangible investments and human resources.

Key Words: Intangible investments, human resources, endogenous sunk costs, industry structure, statistical cluster analysis

JEL Codes: L1, L6, M3, 03

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1. Introduction and outline

Our understanding of the competitive process remains fundamentally incomplete, until we acquire at least some basic knowledge regarding the empirical relationships between the economy and its intangible factors of production. Because intangibles are, by nature, difficult to measure and to value, the lack of reliable, comprehensive and internationally comparable data is a major barrier to broad-scale empirical analysis. In response to the increasing awareness of the important role played by intangible factors of production, the specific purpose of this paper is to make at least some of the `intangibles´ a bit more `tangible´ to quantitative analysis.

This is the first in an attempted series of contributions on `intangible investments and competitive performance at the sectoral level´, initiated by the European Commission s DGIII. The common research plan was created with the intention of coherently matching the analytic claims and the presumed importance of intangible factors of production to the competitive performance of European industries on the one hand, and the practical limitations of the data on the other. The overall programme follows a structuralist approach, comprising three analytic steps. To begin with, this first paper raises the question, whether and to what extent do structural differences exist across industries. In other words: *Do intangible investments matter, as far as industrial structures are concerned?* If the answer is no, the sectoral level will not be meaningful enough to warrant further analysis. As this paper, however, is going to reveal, surprisingly pronounced structures and sharply edged patterns do indeed exist. Applying the new tools generated in this first step, a second paper in the series will focus on the actual impact of intangible investments on variables such as productivity, income, employment and growth or the vertical differentiability of products. In brief, the underlying question can be stated as follows: *Do the structural differences evident in intangible investments really matter for economic performance?* Given the prior observations that structural differences do exist and are indeed of importance to competitive performance, we are then able to answer the third question, which asks: *What do international comparisons of industrial structure reveal about the underlying competitive strengths and weaknesses of European industry?*

This paper is organised as follows: First of all, several general examples illustrate the consequences of the inclusion of intangibles for some major predictions of economic theory. Secondly, a new taxonomy of manufacturing industries, based on typical combinations of factor inputs, is created and documented in detail, revealing many pronounced structural differences related to the intangible factors of production. Thirdly, a complementary taxonomy is also developed, which is based upon data on labour skills and reflects the dimension of human resources. In the final section of this paper, the two taxonomies are applied in a test of the presumed complementarity between intangible investments and the employment of high skilled labour.

It is important to note, that in addition to the initial analytic questions stated above, the creation of new taxonomies in this paper simultaneously serves a special practical purpose within the overall research plan. Reflecting the lack of comprehensive data on intangible investments across a number of different countries or economic areas, it enables us to apply the more easily available basic indicators of economic activity such as value added, employment or trade flows in an economically meaningful way. Stressing the structural determinants of competitive strategy, the new WIFO taxonomy thus offers a sophisticated tool for the analysis of intangible investments and competitive performamce at the sectoral level.

2. Why intangibles matter

During the past decades, several economic disciplines have witnessed a profound reshaping of some of their major theoretic predictions, which at the utmost general level are also characterised by the common inclusion of intangible factors of production in the new generation of models. In an attempt to motivate the more technical empirical analysis, this section collects some supportive, albeit highly stylised, examples of this claim.

Beginning with a well-known example from *Growth Theory*, the conventional Solow-Swan model was famous for its prediction of \`conditional convergence´ (whereby the steady state rate of growth varies across economies, depending on the savings rate, population growth and the shape of the production function). However, the assumptions of constant returns to scale and diminishing returns on each input also implied the eventual end of per capita growth, if there were no exogenous improvements in technology. In contrast, starting with Arrow s (1962) model of \`learning by doing´, the large body of literature on endogenous growth (e.g. Grossman-Helpman, 1991; Aghion-Howitt, 1998) stressed the cumulative nature of knowledge, the incentives for purposeful investment in its creation and spillovers to the rest of the economy through diffusion. Long-term growth then is determined by the balance of incentives to innovate, on the one hand (raised e.g. by the degree of cumulativeness and the non-competitive rewards of temporary monopoly power) and its own propensity to generate external benefits, on the other hand. As a consequence, one of the most significant economic implications of the new growth theory which results from explicitly including purposeful investments in the production of new and intangible knowledge (i.e. somewhat difficult to appropriate and therefore a source of spillover) implies that long-term growth remains feasible even in developed countries with high levels of per capita income.

Similarly, in *Industrial Organisations,* the notion of `endogenous sunk costs´ (Sutton, 1991) which reflects the irreversible nature of intangible investments in such areas as advertising or research brought about a major leap forward in our understanding of the evolution of market structure. Within that framework, advertising and R&D are understood as being typically sunk investments intended to raise the consumer s willingness to pay for the firm s output. Broadening the traditional concept of the production function, these can be considered productive inputs to the generation of revenue. The distinctive feature is that for the firm, advertising and R&D are the strategic variables of choice. In contrast, the sunk costs involved in physical investments (e.g. the acquisition of new plants at the minimum efficient scale) are determined exogenously by the underlying technology and consequently are equal across firms. Investigating the effect of a rise in market size on supplier concentration, Sutton shows that exogenous sunk costs are reflected in a general and unbounded tendency of the equilibrium level of concentration to decline with the ratio of market size to setup cost. Ceteris paribus, growing market demand thus produces an increasingly fragmented market structure. However, depending on the responsiveness of demand to advertising and R&D, endogenous sunk costs allow for a competitive escalation of expenditures, raising the equilibrium level of sunk investments in the particular industry. Thus, even in the presence of increasing market size, sunk costs can effectively act as barriers to further entry and may offset the tendency towards fragmentation. In short, the presence of endogenous sunk costs such as intangible investments in advertising and R&D implies that *under very general conditions a lower bound exists to the equilibrium level of concentration in the industry, no matter how large the market becomes*. (Sutton, 1991, p. 11)

Apart from exogenous technological boundaries, intangible investments such as advertising and R&D, as well as user-specific supplier services, more generally define the potential scope for product differentiation and surplus income. Besides industrial organisation, this aspect is of special importance in two complementary fields of *International Economics*, i.e. trade theory and the theory of multinational enterprises. On the one hand, product differentiation (and thus intangible investments) is a necessary precondition for the `escape´ of high-wage countries from the traditional prediction of factor price equalisation and the according downward pressure on labour incomes in trade theory. This downward pressure on factor incomes might otherwise be expected from the increasing integration of global markets accelerated by the high mobility of international capital flows. On the other hand, we could also take the theory of multinational enterprises into consideration, by which locationally bounded comparative cost advantages can only explain a (rather small) fraction of total transborder investment flows. On the contrary, the motivation for multinational investment is largely explained by the exploitation of firm-specific assets such as accumulated organisational and technological knowledge or reputation and the creation of brands (see e.g. Dunning, 1994 or Caves, 1996). Again, it is precisely their intangible, non-commodity-like nature, which makes these assets difficult to trade and therefore largely specific to the firm. As a consequence, such assets are often exploited more effectively through organisation within the firm rather than purely contractual relationships through exchange on (factor) markets.

The creation of firm-specific competitive advantages by intangible investments and knowledge-based resources can also be linked to Austrian Economics (Kirzner, 1998) and related evolutionary models of *Schumpeterian Competition* (Metcalfe, 1998). Both share an emphasis on the necessary diversity of a firm s capabilities and behaviour, driving the dynamics of innovation and selection by differential growth in the marketplace. Combining the resource-based view of the firm with more recent developments in innovation research, competitive advantage therein is often defined in terms of the firm s specific `dynamic capabilities´, i.e. the subset of the competencies/capabilities which allow the firm to create new products and processes, and respond to changing market circumstances. (Teece-Pisano, 1998, p. 197) This definition suits our purpose particularly well, since it stresses not only the responsiveness to `fast moving external conditions such as technological change and shifting consumer tastes, but also the key role of strategic choices (among them most notably the choice in which competitive assets to invest) as the fundamental criteria of competitive selection. The particular relevance of the latter relates to the presumed pro-active capability of firms to *increase perceived quality* and thus also to raise the willingness of consumers to pay for their products: Within rather wide limits it is reasonable to suppose that consumers tastes are formed by the range of commodities which are available to them or, at least, about which they know. As a consequence, the real entrepreneur does not take demand as a `given´ but rather as something he ought to be able to do something about. (Penrose, 1959, p. 80)

Table 1: Why intangibles matter

Some stylised examples of major differences in economic predictions..	..exclusively based on tangible factors of production/revenue generation	..considering intangible factors of production/revenue generation
Growth theory	Decreasing returns on factor inputs; convergence in per capita income; zero-growth for high income countries	Allowing for non-decreasing returns, divergence, and sustainable growth (Arrow, 1962; etc.)
Industrial Organisation	Increasing market size necessarily leads to increasing fragmentation	Lower boundaries to market concentration, as market size increases (Sutton, 1991)
Multinational Enterprises	Motivated by locational cost advantages, better access to markets & low transport costs	Multinational investments in order to exploit firm specific assets (e.g. Dunning, 1994)
International Trade	Homogenous goods; comparative cost advantages & factor price equalisation	Increasing returns to scale; product differentiation & differential incomes (Krugman, 1979, etc.)
The nature of competition: neo-classical versus evolutionary models	Static equilibrium and allocative cost efficiency	Locally progressive change from dynamic competition (Metcalfe, 1998)

With respect to these pro-active sources of entrepreneurial opportunity, there are two archetypes of intangible investments capable of raising the perceived quality of products. Research and innovation (i), which enables firms to turn aside the process of `creative destruction´ and thrive on the novelty which might otherwise have destroyed them. (Penrose, 1959, p. 115) And more generally, advertising or marketing (ii), which is perhaps of greatest importance for firms whose productive processes are either highly specialised with respect to the kind of product for which they are suitable, or are simple and easily imitated and of a kind where research yields little that provides particular firms with any competitive advantage. (Penrose, 1959, p. 116)

Despite their admittedly short and simple presentation, these examples bring to surface a broad but seemingly robust interpretative framework of related pairs of opposites, characterised by terms such as `exogenous and endogenous´, `natural or strategic´, and `location-bound vs. firm-specific´, which emerge in different fields of economic theory. The reason why these examples have been included in this introduction, is that all of them are also related to the distinction between `tangible and intangible´ factors of production interpreted more broadly in terms of revenue generation. In particular, the intangible nature of some services or productive resources implies a low or inefficient ability to be traded on the markets, rendering them dependent on strategic choices to invest in their generation within the specific firm. Since such `strategic´ choices are sensitive to public policy, this distinction deserves even more attention, stressing the presence of complementary institutions, services and skills as a precondition for competitive success, high income and sustainable growth.

3. The new WIFO taxonomy

3.1 References and novel features

This section presents a new taxonomy of manufacturing industries based on typical patterns of factor input combinations. The new approach focuses on the distinction between tangible and intangible factors of production/generation of revenues. We go considerably beyond the popular, manifold `high-tech´ versus `low-tech´ distinctions, which perhaps have found their most comprehensive update in *Hatzichronoglou* (1997). In contrast, the new taxonomy presented in this paper is based on two entirely different sources of inspiration: First of all, *Schulmeister s* (1990) extension of a classification by *Legler* (1982) must be mentioned in light of its successful combination of the usual high-, medium- and low tech differentiation with a more comprehensive coverage of factor inputs such as capital investment, labour costs, research expenditures and energy consumption. Secondly, investigating the economic impact of endogenous sunk costs at the industry level, *Davies and Lyons* (1996) introduced and applied an influential taxonomy based on a firm s intangible investments in advertising and R&D[1]. All of these taxonomies rely on traditional cut-off procedures, by which a certain discriminatory edge is defined exogenously by the researcher before the analysis. In choosing not to use more powerful statistical tools for categorising multidimensional data, the underlying structure within the data is more or less presumed, rather than extensively explored. In contrast, it is precisely on such an exploration that this section will focus.

In short, the new taxonomy is characterised by three distinctly novel features: (i) From an analytic perspective, it is the particular choice of variables, which reflects exogenously given technology on the one hand, as well as the firm s targeted expenditures on innovation and marketing on the other. It thus combines elements of *Schulmeister* (1990), and *Davies and Lyons* (1996). (ii) From a methodological standpoint, the new taxonomy is the first industry classification known to the author, which uses statistical cluster techniques to reveal typical patterns, hidden within the data, simultaneously across a multidimensional set of variables. This is clearly a more powerful tool than the traditional cut-off procedures.[2] (iii) Finally, from a purely practical perspective, the new taxonomy is the first of its kind to target the 3-digit level of E ROSTAT´s ACE rev.3 classification of industries.

3.2. Choice of variables

In any attempt to classify and categorise a number of observations, the most sensitive step is the initial decision concerning the appropriate dimensions against which individual cases should be measured and discriminated. The primary purpose of the current taxonomy is to

[1] See also *Davies, Rondi and Sembenelli* (1998) for a more recent application.

[2] See also Peneder (1995).

provide an applicable tool for empirical analysis, with regard to comparative studies of international patterns in production and trade, as well as econometric tests on the impact of intangible investments on competitive performance and structural change. Both applications, whether comparative or analytic, are critically based upon the assumption that an economy s observable patterns of specialisation mirror its underlying strengths and weaknesses, be they either comparative cost advantages attributable to relative factor abundance or sources of dynamic economies of scale.

As a consequence, the particular choice of variables reflects the different strategic options with which firms can increase their competitive performance in the market place. Following the stylised distinction of two opposing poles in the first section of this paper, the new taxonomy tracks both (i) comparative cost advantages stemming from exogenous and location dependent factors such as relative endowments with capital and labour; and (ii) firm specific advantages stemming from targeted investment in intangible assets such as advertising and R&D. For obvious reasons, the complex issues of competitive advantage from firm specific organisational knowledge cannot be included in this cross-sectoral setting. In this sense, our concept of the firm remains closer to the traditional micro-economic focus on the production function, albeit interpreted more broadly as the relationship between factor inputs and revenue generation, in contrast to the more simple relation of inputs to the mere quantity of output. As a consequence, dynamic capabilities are created by purposeful investment in intangible assets, such as goodwill and innovation. If we assume, however, that organisational tasks will be more difficult and complex, the more `fast moving´ the business environment is, we might reasonably expect a high degree of correlation between organisational complexity (and thus the organisational capabilities required) and e.g. the research intensity of production.

In addition to an elaborate economic rationale, statistical cluster analysis requires a clear concept of geometric space that allows for a meaningful measurement of distances between observations. Variables have to be chosen in a way that spans the independent dimensions of the phenomenon under investigation. Ideally, basis vectors should be orthogonal, which implies a Cartesian co-ordinate system, whereby the respective axes fulfil the condition of orthonormality. The minimum requirement is their linear independence.[3] In the following cluster analysis, orthonormal space will be restricted to variables representing distinct input combinations in the generation of a firm s revenues.

For the calculation of mean values for the latest years available in each case, the following variables were chosen:

1. *Labour intensity*: Average ratio of gross wages and salaries to value added from 1990 to 1995.
2. *Capital intensity*: Average ratio of total investments to value added from 1990 to 1994.
3. *Advertising sales ratio*: Average ratio of advertising outlays to total sales from 1993 to 1995.
4. *R&D sales ratio*: Average ratio of expenditures on research & development to total sales from 1993 to 1995.

Due to the lack of equally disaggregated data for the European nion across all four dimensions, data refer exclusively to S-manufacturing industries. The data on labour intensity and capital intensity stem from DEBA-GEIE, the data on research expenditures and advertising outlays from COMP STAT. While data from DEBA-GEIE were provided by statistical offices in an aggregated form at a 3-digit level, information from COMP STAT is based on the balance sheet data of individual firms. Total sales calculations are all based exclusively on those firms, which actually report their R&D or advertising outlays. This introduces some distortions caused by non-reporting firms. However, ex post inspection of the data revealed that at least in industries where investment in advertising or R&D is particularly pronounced, coverage also is high, indicating particularly strong

[3] Violations of the underlying assumption of orthonormal space are a serious concern in cluster analysis. The number of linearly independent vectors determines the dimensionality of the space spanned. In general, a set of vectors is linearly independent, if no vector can be represented by a linear combination of other vectors in the set. Orthogonality additionally requires the scalar product of the two basis vectors to be zero. However, as long as they are linearly independent, a number of p basis vectors can span a p-dimensional space without being orthogonal. In this case, space is referred to as being *oblique* (spanned by oblique basis vectors). Thus, any point in p-dimensional space can be expressed in terms of an orthonormal or an oblique basis, respectively (*Sharma*, 1996, p. 31). It is also possible to change the basis by according manipulations. But representation using an orthonormal basis is easier to work with, and therefore is usually applied in multivariate analysis.

incentives to report the according information to the company s shareholders. Indeed, in industries characterised by high levels of research expenditures, almost all firms report their R&D expenditures. To a lesser extent, the same tendency can be observed with respect to advertising outlays.

Another critical feature is the exclusive choice of S-data, which opens two areas of concern with the potential to cause unpleasant distortions or noise in the data: First of all, the underlying assumption that S-input combinations are representative of all the other economic areas under investigation may not be valid, especially when the same 3-digit grouping comprises very heterogeneous activities. Secondly, the application of S-data on a European classification scheme implies that the data have to be transformed from S-SIC to ACE rev.1. The data on wages & salaries, as well as on net investment flows, have already been transformed by E ROSTAT-DEBA. Firm data on advertising and R&D have been transformed by WIFO at the 4-digit level and then aggregated to the 3-digit level. The correspondence table was supplied by E ROSTAT.

Table 2: Correlation of the chosen variables

Correlations

		ADI_Z	KI_Z	LI_Z	RDI_Z
Pearson Correlation	ADI_Z	1,000	-,316**	-,290**	-,142
	KI_Z	-,316**	1,000	-,240*	,005
	LI_Z	-,290**	-,240*	1,000	-,198*
	RDI_Z	-,142	,005	-,198*	1,000
Sig. (2-tailed)	ADI_Z	,	,001	,003	,160
	KI_Z	,001	,	,016	,961
	LI_Z	,003	,016	,	,048
	RDI_Z	,160	,961	,048	,
N	ADI_Z	100	100	100	100
	KI_Z	100	100	100	100
	LI_Z	100	100	100	100
	RDI_Z	100	100	100	100

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

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

All four variables were used in their standardised form, i.e. transformed by calculating the difference to the mean divided by the variables standard deviation. Thus, the overall effects of differences in the size of the variables were eliminated and adjustments were made for differences in their variability. A final point of concern was potential correlations between variables, which require more sophisticated techniques for the appropriate measurement of distances, such as the *Mahalanobis Distance*, which takes into account the covariance among variables.[4] However, in the current data set, correlations are low or non-existent (Table 2). The highest negative correlation is in the relationship between advertising and capital investment, where the value of -0.316 implies that no more than 10 of total variation in the variable for advertising outlays can be explained by opposing variation in the variable for capital investment. o significant positive correlation occurs at all.

3.3 Statistical clustering

Cluster analysis produces a classification scheme of individual observations, depending on their relative similarity or nearness to an array of variables. The basic idea is one of dividing a specific data profile into segments by creating maximum homogeneity within and maximum distance between groups of observations. It is important to remember that despite its mathematical sophistication, cluster analysis represents a heuristic method for the exploration and identification of underlying patterns in the data. Although its results may be applied as valuable dummies or shift parameters in inferential analysis, cluster analysis is not able to prove any hypothesis by itself. nfortunately, there is also no single objective criteria for optimisation, which could guide the researcher through the many choices concerning measurement and appropriate algorithms. However, despite this lack of `objective´ benchmarks, the popular accusation of being able to reproduce `any´ outcome desired is certainly exaggerated - at least as long as no differential weighting of the variables is applied. [5]

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[4] If variables are uncorrelated and variances equal to one, Mahalanobis Distance reduces to the common squared Euclidean Distance (SED).

[5] Applying a metaphor, the scope of potential manipulation may be best compared to analogue photography, where the choice of the appropriate angle of perspective or the combination of focal length and the shutter release plus the use of some sort of polarisation filter may increase desired contrasts similar to the choice of distance measures and particular cluster algorithms. However, the underlying objects or patterns must still be in the data, if they are to be detected. Sticking to this metaphor, allowing for different

The most important advantage of statistical cluster techniques relative to conventional cut-off methods of dividing given data sets into distinct groupings, is their endogenous determination of the edges and boundaries that discriminate between observations, thus supporting the exploration and screening for regularities from within the initial data set. Especially when dealing with multidimensional phenomena, the analytical capacity of cluster analysis by far surpasses that of traditional cut-off procedures.

3.3.1 First partition: Optimisation methods

After selecting the set of variables, an optimisation cluster technique, based on the minimisation of within-group dispersion, is used to classify one hundred ACE 3- digit manufacturing industries into clusters of maximum homogeneity. The set of observations is divided by a pre-defined number of clusters g. Cluster-centres are then estimated for each group; they are the vectors of the means of the corresponding values for each variable. The optimisation criterion is given by the trace of the matrix of within group dispersion W (of the dimension p x p), which consists of vectors x_{ij} for the jth observation in the ith group and the according cluster-centres:

(1) $$W = \frac{1}{n-g}\sum_{i=1}^{g}\sum_{j=1}^{n_i}(x_{ij}-\overline{x}_i)(x_{ij}-\overline{x}_i)'$$

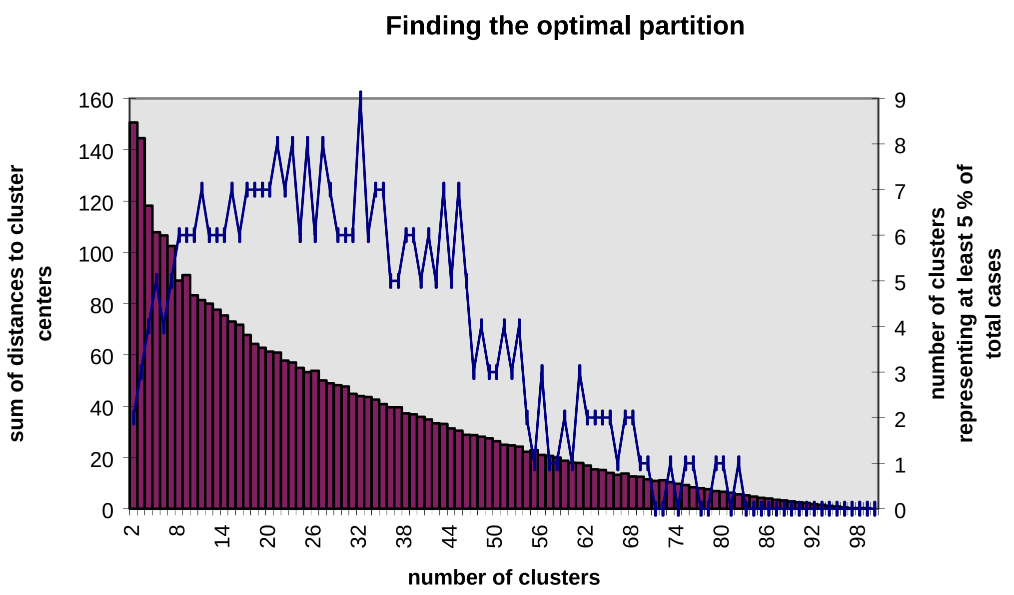
Trace (W) is minimised with iterative algorithms, whereby the position of the cluster-centres are varied until the process converges. The number of clusters g was initially chosen by calculating the sum of the distances to cluster centres for all possible partitions from a minimum of only 2 clusters up to a maximum of 100. The purpose was to identify any obvious kinks or optimal partitions in the resulting distribution. However, we were unable to find any indisputable elbow or kink in the distribution that would determine the choice of the number of clusters (Figure 1).

Following an approach developed in an earlier paper (Peneder, 1995), the following self-binding rule of thumb was applied: *Choose the lowest number g that maximises the*

weightings of the variables would correspond to digital photography, in which case the potential scope for manipulation would indeed be very large.

quantity of individual clusters which include more than 5% of the observed cases. According to this rule of thumb, the number g 32 clusters was chosen as the first partition, with 9 clusters comprising more than 5 of total observations, whereas the others only applied to individual outlying cases. However, 32 different clusters do not yet constitute a helpful aggregation for a final interpretation of the data. Therefore, a more complex hierarchical cluster algorithm was applied in a second step.

Figure 1: Choice of first cluster partition



3.3.2 Second partition: Hierarchical clustering

Hierarchical cluster techniques require a heuristic interpretation of the surfacing patterns, which can be supported graphically. When the number of observations is too large, this work becomes increasingly arbitrary. The purpose of the first partition therefore has been to reduce the number of cases and to provide a more aggregate picture by the according cluster centres (Table 3).

In the second step, the resulting 32 clusters of the first partition enter a hierarchical clustering algorithm as observations, with their corresponding cluster centres as values. In the current analysis, the *cosine of the vectors of the variables* was applied. This is a typical measure of similarity in patterns instead of absolute distances, relating two distinct observations i and j across their respective vectors of k variables:

(2)
$$similarity_{ij} = \frac{\sum_k (x_{ik} x_{jk})}{\sqrt{\sum_k (x_{ik}^2) \sum_k (x_{jk}^2)}}$$

In the following agglomerative algorithm, all observations are initially treated as independent single clusters. In the iterative process, the similarity of all pairs is compared, and those pairs exhibiting maximum similarity are grouped together to form a common cluster. *Average linkage* between groups measures the similarity of the newly formed agglomeration according to the average distance of all single pairs between an observation outside and each observation inside the cluster. The outcome is a hierarchical structure, beginning with many single observations that finally unite at different levels, until all are unified by one single trunk. The closer individual clusters are to the origin, the more they are clumped together by the vertical lines in the *dendrogram*, and the more similar are their underlying patterns of input combinations.

Applying a number of variations on both (i) the measures of distance and (ii) the clustering algorithm itself, two different outcomes typically appeared: First of all, a surprisingly consistent and sharply edged structure of about 4 clusters and some outlying satellites emerged for a number of variations for at least two measures of similarity (cosine and correlation of vectors of values, respectively) and a variety of different algorithms (e.g. average linkage between groups, complete linkage, etc.; see Figure 2). In all other cases, the clustering process failed entirely, due to the so-called `chaining´ effect. This happens when no useful partition emerges, because the algorithm continuously adds one individual case after another to the same single trunk of observations (Figure 3).

Table 3: Cluster centres resulting from a first partition

Cluster	Wages & salaries	Physical capital	Advertising	R&D
1	1,10	0,26	-0,37	-0,85
2	-0,60	0,20	0,98	-0,52
3	-0,24	-0,29	-0,91	3,55
4	0,65	-0,52	-0,63	1,20
5	0,92	-0,32	2,64	-0,14
6	-1,79	-0,07	1,47	-0,74
7	-0,93	1,05	-0,43	-0,82
8	-2,54	0,26	-0,43	-0,48
9	0,16	-0,80	2,20	-0,30
10	-3,12	-1,40	1,50	-0,85
11	-1,00	-0,10	0,18	2,00
12	1,01	0,72	0,38	-0,74
13	-1,16	1,90	-0,79	0,61
14	-2,26	-0,57	2,23	0,32
15	-0,47	-0,48	4,22	0,40
16	0,12	0,17	-0,50	0,06
17	0,70	-0,42	0,13	-0,21
18	0,47	-1,16	-0,13	-0,20
19	-2,08	0,14	0,84	5,49
20	-0,57	-0,41	-0,66	0,09
21	-0,43	1,26	-0,39	2,12
22	0,58	-0,85	1,03	-0,64
23	1,98	-1,04	-0,28	-0,60
24	0,82	1,41	-0,67	-0,02
25	-1,18	0,30	-0,52	0,87
26	1,14	-0,54	-0,60	-0,61
27	-2,02	5,23	-0,96	-0,75
28	0,65	-0,19	-0,59	-0,11
29	-0,61	4,00	-0,76	-0,56
30	-0,43	-0,10	-0,94	2,47
31	-0,50	-0,72	0,89	0,14
32	0,14	1,44	-1,05	-0,65

Figure 2: Dendrogram using average linkage between groups and the cosine of vectors of values

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* * * * * * H I E R A R C H I C A L   C L U S T E R   A N A L Y S I S * * * * * *

Rescaled Distance Cluster Combine

   C A S E    0         5        10        15        20        25
  Label  Num  +---------+---------+---------+---------+---------+

          11   -+---+
          19   -+   +-+
           3   -+---+ +---+
   TDI    30   -+     I   +-----+
          21   -------+   I     +-------------+
          25   -----------+     I             +-----+
           4   -----------------+             I     I
           8   ---------------+---------------+     I
          20   ---------------+                     +-----------+
          27   -+---+                               I           I
          29   -+   +-+                             I           I
          13   -----+ +---------+                   I           I
    CI     7   -------+         +-------------------+           I
          24   -----+-----+     I                               I
          32   -----+     +-----+                               I
          16   -----------+                                     I
           2   ---+-----+                                       I
           6   ---+     +---------+                             I
          10   -----+-+ I         I                             I
          14   -----+ +-+         I                             I
    MDI   31   -------+           +---------------------------+ I
           5   ---+               I                           I I
           9   ---+-----+         I                           I I
          15   ---+     +---------+                           +-+
          22   ---------+                                     I
           1   -------+-------------+                         I
          12   -------+             I                         I
    LI    17   -+-----+             +-------------------------+
          23   -+     +---+         I
          26   ---+---+   +---------+
          28   ---+       I
          18   -----------+
```

TDI..research intensive (`technology driven´); MDI ..advertising intensive (`marketing driven´); CI.. capital intensive; LI.. labour intensive

Figure 3: Example of failed clustering due to the chaining effect (average linkage between groups; squared Euclidean distances)

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* * * * * *H I E R A R C H I C A L  C L U S T E R   A N A L Y S I S* * * * * *

                      Rescaled Distance Cluster Combine

   C A S E    0         5        10        15        20        25
  Label  Num  +---------+---------+---------+---------+---------+

          16   -+
          28   -+-+
          20   -+ I
           4   ---+
          17   -+ I
          18   -+-+---+
          22   -+ I   I
           1   -+ I   I
          26   -+-+   +---+
          12   -+ I   I   I
          23   ---+   I   I
           5   -+---+ I   I
           9   -+   +-+   +---+
           2   -+---+     I   I
          31   -+         I   I
          24   -+-+       I   I
          32   -+ +-+     I   +---+
           7   ---+ +-----+   I   I
          13   -----+         I   I
           3   -+---+         I   I
          30   -+   +---------+   I
          11   ---+ I             +-------+
          25   ---+-+             I       I
          21   ---+               I       I
           6   ---+               I       +-----------+
          14   ---+-----+         I       I           I
          10   ---+     +---------+       I           +---------+
           8   ---------+                 I           I         I
          15   ---------------------------+           I         I
          27   -----+---------------------------------+         I
          29   -----+                                           I
          19   -------------------------------------------------+
```

3.4 The resulting taxonomy

The graphical representation of relative similarity in the dendrogram of Figure 2 provides a surprisingly sharp-edged discrimination of four broad categories, each one characterised by a rather pronounced reliance on one of the four input-dimensions. Since no successful alternative pattern emerged, this outcome constitutes the basic pattern for defining the final taxonomy.

pon locating the according cluster centres in Table 3, interpretation of the dendrogram in Figure 2 is straightforward: the first grouping of industries ranges from cluster 11 to cluster 4, and is characterised by particularly high expenditures on research & development; a second grouping ranges from cluster 27 to 32, and is unequivocally linked to particularly high rates of investment in physical capital; the span of the third distinct grouping is from clusters 2 to 22, and exhibits high shares of advertising outlays. Finally, the block ranging from cluster 1 to 18 comprises cases with particularly high labour costs.

Clusters 16, 20 and 28, which all include quite a great number of individual industries, could in principle be allocated to their respective groupings of research, capital, or labour intensive industries. However, a closer look at their input combinations reveals that these industries are mostly distinguished by their lack of a pronounced reliance on any of the four factor inputs. In consideration of their position on the relative fringes of their respective agglomerations, they have been grouped together in a residual category, labelled \`mainstream´ manufacturing, representing more or less the input combination of a \`typical´ 3-digit manufacturing industry. This also provides a convenient comparative group for econometric exercises.

There is one exception to the general robustness of the results with regard to variations in clustering algorithms and measures of similarity: cluster 8, which comprises only one single industry - namely agrochemical products. Despite its rather average share of research expenditures in total net turnover, it was allocated to the grouping of research intensive industries, as a result of overall similarities in particular combinations across all four factor inputs. However, when different measures of distance were tried, it was also sometimes more closely associated with capital intensive production. Its ultimate classification within the grouping of research intensive industries rests on reported results from patent analysis across technology fields (Andersen, 1997) and specific industry monographs (Achilladelis-Schwarzkopf-Cines, 1987), which equivocally stress its particularly high shares in overall innovative activities. In Andersen s comparison of accumulated patent stocks across a total of 399 patent classes, agriculture chemicals even hold the 10^{th} position in a ranking of \`technological size´ for 1990. As a consequence, she concludes that these have been among the fastest growing technological sectors throughout this century and have never grown as much in accumulated patent stock as in recent times . (Andersen, 1997, p. 38).

In the end, precisely 100 ACE 3-digit manufacturing industries were categorised under the following five, mutually exclusive groupings (Table 7):

1. *Mainstream manufacturing* (i MM): This residual category was created out of 25 industries, in which input combinations did not show a pronounced reliance on any particular input factor. Summing up all manufacturing industries in the European nion, apan and the SA in 1996, this group generated 24.54 of total value added, 27.33 of employment, 24.09 of its exports, but only 15.83 of imports. The archetypal example is the *machinery* sector. Among others, this group also includes *articles of paper*, *plastic products*, *electronic equipment* and *motorcycles*.

2. *Labour intensive industries* (i LI): Comprising 25 individual 3-digit industries, the common share of total employment in the triad in 1996 amounts to 22.1 . This is contrasted by a rather low share in total value added of about 14.6 . Its shares in the total exports and imports of the triad are 10.2 and 15.6 , respectively. Typical examples are such sectors as *textiles & clothing*, *wood processing*, *construction material* and *metal processing*.

3. *Capital intensive industries* (i CI): In this subgroup, only 9.9 of the triad s total manufacturing employment produces 13.4 of its value added. A share of 16.9 of total exports corresponds to 17.5 of imports. Typical examples are *pulp & paper*, *refined petroleum*, *basic chemicals* and *iron & steel*.

4. *Marketing driven industries* (i MDI): This category comprises 23 advertising intensive industries, together accounting for 22.2 of the triad s total value added and 22.1 of total employment. This is in sharp contrast to the low shares of only 10.0 in the

triad s total exports and 14.1 of total imports. The archetypal example is the *food* sector, which is allocated entirely to this category. Other industries within this category produce articles associated with leisure and entertainment such as *perfumes*, *sports goods*, *musical instruments* or *games & toys*.

5. *Technology driven industries* (i TDI): The 14 industries within this group are characterised by particularly high expenditures on R&D and account for 25.3 of total value added as well as 18.6 of total employment in the triad. Research intensive goods are more highly traded than the products of any other category. Although similar in size to the other categories with regard to value added and employment, their share in total exports and imports amounts to an outstanding 38.8 and 37.0 , respectively. Industries concentrate around three distinct technology fields: (i) *chemicals and biotechnology*; (ii) *new information & communication technologies*, and (iii) *vehicles for transport*.

Table 4: Shares in manufacturing: E - apan- SA 1996 in

Industry type	Value added	Employment	Exports	Imports
Mainstream Manuf. (MM)	24.5	27.3	24.1	15.8
Labour intensive (LI)	14.6	22.1	10.2	15.6
Capital intensive (CI)	13.4	9.9	16.9	17.5
Marketing driven (MDI)	22.2	22.1	10.0	14.1
Technology driven (TDI)	25.3	18.6	38.8	37.0
Total manufacturing	100	100	100	100

Source: Peneder for European Communities (1998).

Like any broad classification, this new taxonomy must be interpreted with some care, since industries within the five categories are still very heterogeneous in nature. One particular concern can be raised with regard to the surprisingly neat designation of cases into each of the four chosen dimensions. Certainly, all the industries produce their output using particular combinations of more than one factor. Advertising, in particular, is often modelled as a complement to vertical product differentiation, in order to provide information to consumers about the quality and innovative features of the product.[6] This tendency is especially relevant in the cases of *pharmaceuticals* (cluster 19) and *optical instruments* (cluster 11) under the heading of research intensive industries, as well as *detergents* (cluster 14), *games & toys* (cluster 15) and *publishing* (cluster 31), which ultimately were labelled advertising industries. Similar combinations can also be found with regard to the other input variables (see Table 3). However, in the final clustering stage, no such pattern of an especially pronounced and characteristic combination of factor inputs, supporting the introduction of an additional category, emerged.

3.5 Characterisation in factor space

This section intends to provide a more precise understanding of the systematic patterns in the typical combinations of tangible versus intangible inputs to production. First, summary statistics of the distribution of individual industries within the five groups are displayed in boxplot charts. Secondly, a non-parametric analysis of variances is used to test for the significance of differences across industry types with regard to each of the four variables.

Simultaneously displaying information about the shape and the dispersion of a distribution, \`boxplots´ provide a convenient mode of summarising descriptive statistics (Figures 4 to 7). The box itself comprises the middle 50 percent of observations. The line within the box is the median. The lower end of the box signifies the first quartile, while the upper end of the box corresponds to the third quartile. In addition, the lowest and the highest lines outside the box indicate the minimum and maximum values, respectively. Maximum values do not include outliers, which are separately indicated. For each of the four dimensions, the boxplots immediately illustrate one striking characteristic of the new taxonomy: in three of the four input-dimensions, there is one single group which absorbs by far the largest amount of total variation across industries. Besides justifying the rather uni-dimensional shortnames, which invoke a rather convenient interpretation for each grouping, we can also take this as a first and strongly supportive observation regarding the overall accurateness of the classification.

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[6] See for example Davies-Lyons (1996).

The boxplots also show that *labour intensity* is the one variable with the least clearly cut discrimination and which exhibits the most variation within each grouping. All five categories include individual industries with high shares of labour costs in total value added, comparable to the mean value for the distinct grouping of labour intensive industries. But even in this case, inspection of the other boxplots reveals what constitutes the distinct feature of the group of so-called labour intensive industries. And that is the particular combination of high labour costs in combination with the lack of any pronounced reliance on complementary investments either in physical capital or the two types of intangible inputs to production.

In contrast to labour intensity, the boxplots for the three other variables tell a different story: As can easily be seen, the isolation of particular *capital* intensive industries within a distinct industry type significantly reduces overall variation. The same applies to *expenditures* on *advertising* or R&, where all the industries with the greatest dependence on a particular input have also been classified within their proper category. Additionally, mainstream manufacturing e.g. seems to exhibit a kind of minimum threshold for research expenditures, which puts its overall research effort ahead of capital- and labour intensive as well as marketing driven industries.

The boxplots already indicated that the new categories fit quite neatly into the four dimensions of factor space. A more rigorous testing can be provided by non parametric tests on the significance of observable differences. This corresponds essentially to an F test, in which an estimate of the *between-groups variance* is compared with an estimate of the *within-groups variance* by dividing the former with the latter. If this ratio exceeds a critical value in the F distribution table, the hypothesis that the two groups exhibit the same mean values can be rejected at the given level of significance. The essential reasoning behind this analysis of variance is, that if the groups come from the same population, then the between-groups variance should be similar to the within-groups variance.[7] The higher the F ratio is, the more unlikely it is that the differences between the means are due to chance.

---

[7] The total amount of variance can be thought of as comprising two elements: (i) the explained variance, which is due to the independent variable represented by the five industry types, and (ii) the error or residual variance, which is due to other factors. The larger the between-groups (i.e. explained) estimated variance is relative to the within-groups (error or residual) estimated variance, the higher the value of the F ratio will be.

Figure 4: Boxplot for labour intensity

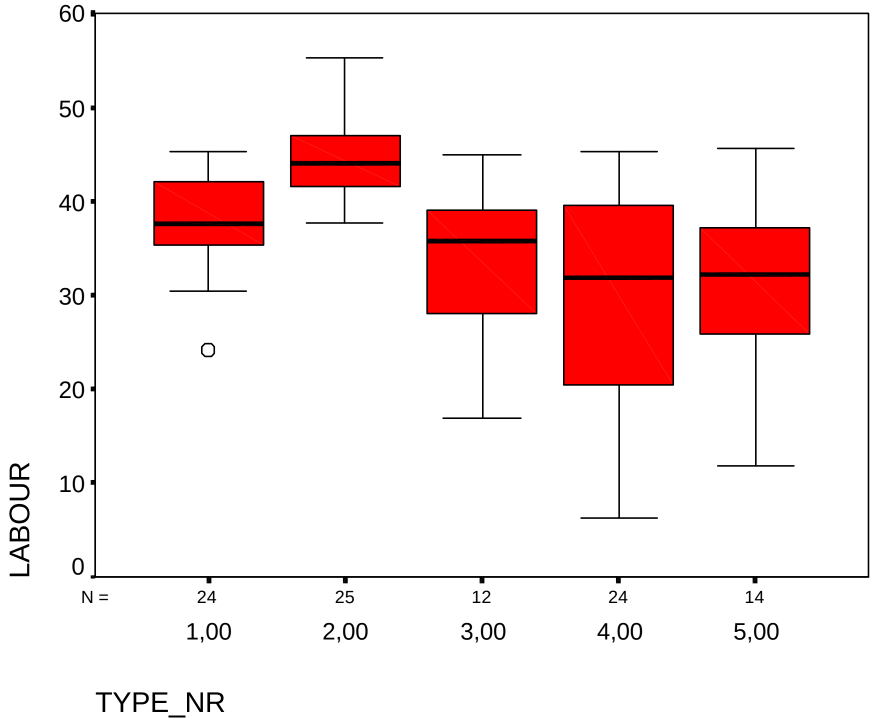
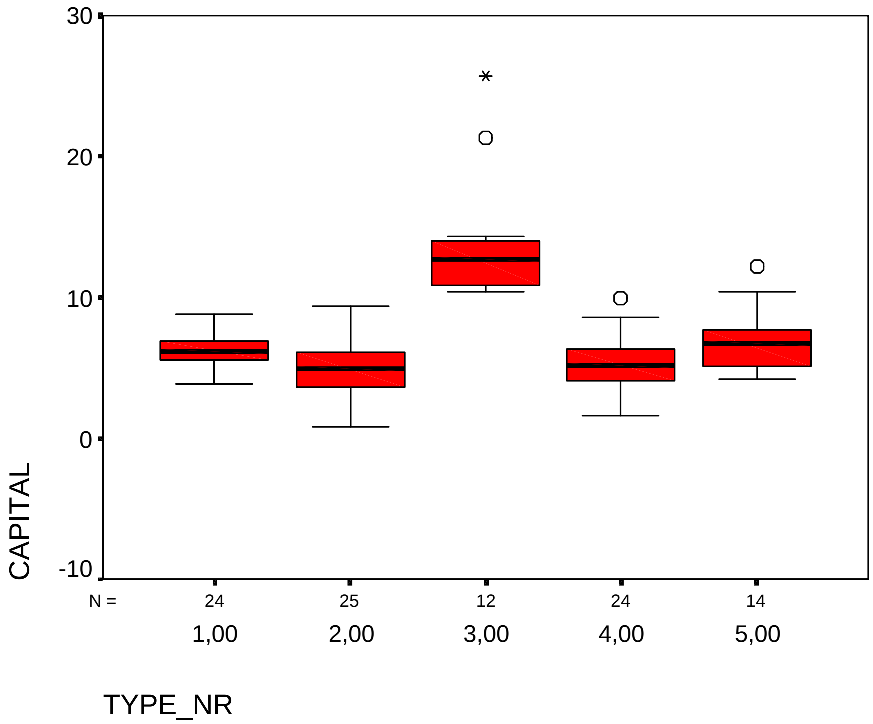


Figure 5: Boxplot for capital intensity



B: 1.. mainstream manufacturing; 2.. labour intensive..; 3.. capital intensive..; 4..marketing driven..; 5.. technology driven industries.

Figure 6: Boxplot for advertising outlays

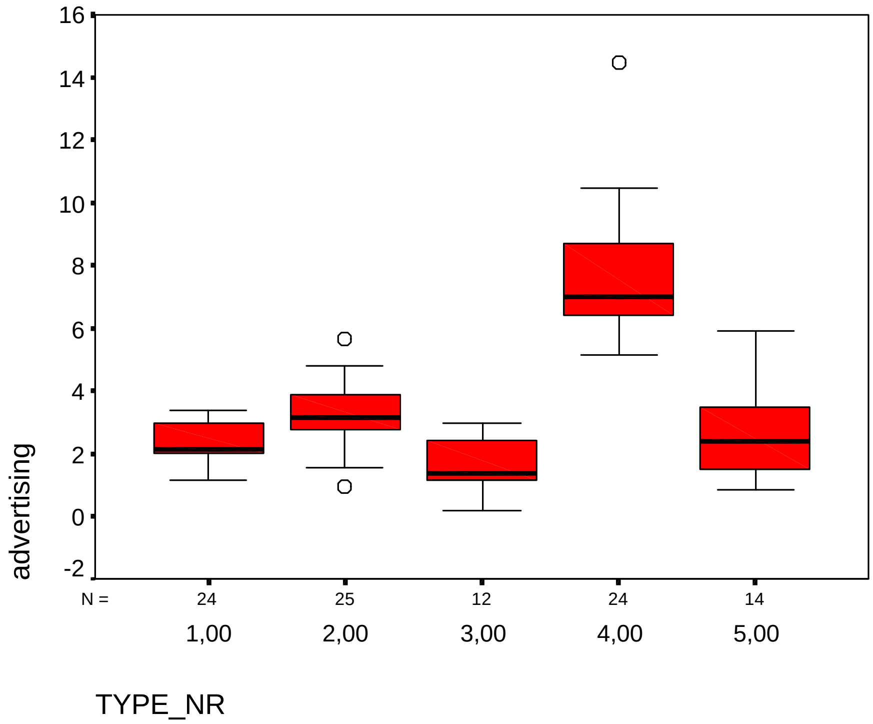
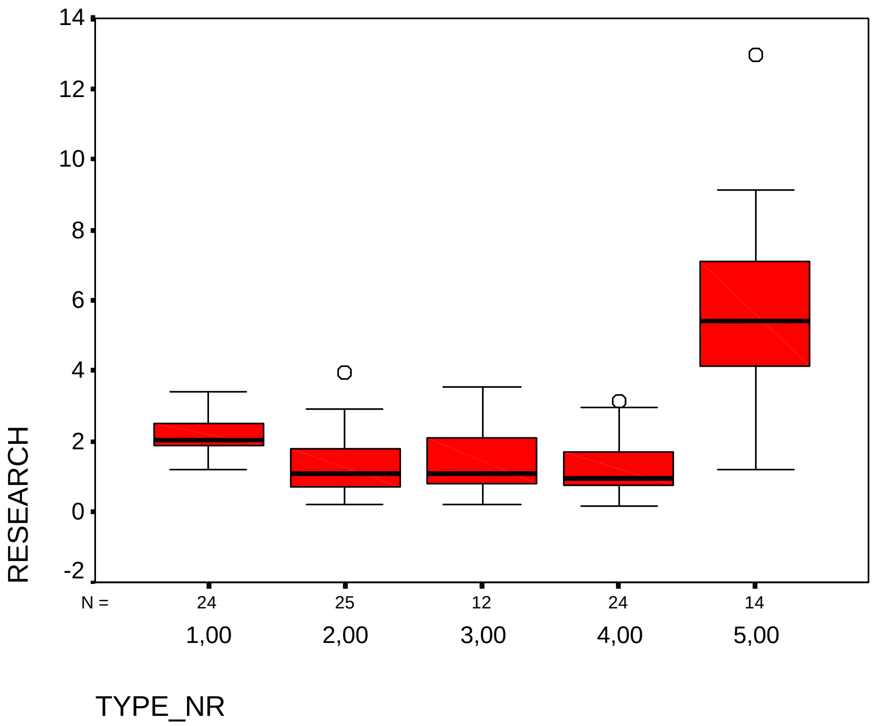


Figure 7: Boxplot for research expenditures



B: 1.. mainstream manufacturing; 2.. labour intensive..; 3.. capital intensive..; 4..marketing driven..; 5.. technology driven industries.

Since the clustering process was targeted on the four distinct input variables, the overall taxonomy has little choice than to vary significantly along them. At a first glance, the whole exercise might therefore seem redundant. However, for our purposes, the truly relevant concern is something different. It is directed towards a more precise understanding of the extent to which the individual pairs of industry types differ. That is, e.g. whether capital and labour intensive industries differ significantly with regard to their respective expenditures on advertising or research, or whether mainstream manufacturing and advertising intensive industries differ with regard to their typical requirements for labour and physical capital. Aside from these comparisons, which involve the grouping with the most pronounced dependence on the variable under investigation, no self-evident predictions can be made a priori. However, Table 5 reveals some additional regularities. Most of them can be associated with the grouping of mainstream manufacturing, which for example are significantly more labour intensive than marketing and technology driven industries and show a higher R&D-sales ratio than all other groupings, except the technology driven industries. Similarly, both are significantly more capital intensive than the labour intensive and marketing driven industries. In short, along the four dimensions of pure labour input, tangible investment in physical capital, and intangible investments in research and advertising, the following regularities appear to be significant:

- *Labour intensity* in mainstream manufacturing is significantly higher than in capital intensive, marketing or technology driven industries. In contrast, there is no significant discrimination between these three groupings.
- With regard to *capital intensity,* the largely similar groupings of technology driven industries and mainstream manufacturing rank significantly higher than labour intensive and marketing driven industries, which again are similar in their low shares of capital investment.
- *Advertising* turns out to be most differentiated across industry types, with the mean ranks significantly higher in labour intensive industries, followed by mainstream manufacturing and technology driven industries (which again cannot be discriminated). Capital intensive industries rank lowest.
- With regard to *research expenditures*, only mainstream manufacturing can make a significant difference, outperforming any other grouping (except for TDIs), for which there can be no further discrimination.

Table 5: on parametric tests for significant differences in factor inputs

Shares in total employment	number of industries	mean rank	Industry type	Mann-Whitney *U* test / Kolmogorov-Smirnov *Z* te			
				MM	LI	CI	MDI
Labour intensity	25	50	MM	-	***	-	*
Median Test: ***	25	79	LI	***	-	***	***
Kruskal-Wallis *H* test: ***	11	37	CI	-	***	-	-
	24	35	MDI	**	***	-	-
	14	35	TDI	**	***	-	-
				MM	LI	CI	MDI
Capital intensity	25	54	MM	-	***	***	**
Median Test: ***	25	35	LI	***	-	***	-
Kruskal-Wallis *H* test: ***	11	93	CI	***	***	-	***
	24	37	MDI	**	-	***	-
	14	58	TDI	-	**	***	**
				MM	LI	CI	MDI
Advertising-sales ratio	24	32	MM	-	***	-	***
Median Test: ***	25	52	LI	***	-	***	***
Kruskal-Wallis *H* test: ***	11	19	CI	**	***	-	***
	24	86	MDI	***	***	***	-
	14	36	TDI	-	**	*	***
				MM	LI	CI	MDI
Research-sales ratio	24	61	MM	-	***	***	***
Median Test: ***	25	38	LI	***	-	-	-
Kruskal-Wallis *H* test: ***	11	39	CI	**	-	-	-
	24	33	MDI	***	-	-	-
	14	88	TDI	***	***	***	***

NB: MM.. mainstream manufacturing; LI.. labour intensive..; CI.. capital intensive..; MDI..marketing driven..; TDI.. technology driven industries

*** significant at the 1% level
** significant at the 5% level
* significant at the 10% level

5. Classifying industries according to labour skills

Analogous to the first taxonomy introduced above, which related intangible investments in advertising and R&D to the more tangible inputs of physical capital and labour, the important aspect of human resources will be captured within a second taxonomy, which can either be linked with the first taxonomy or be applied separately. This time, the taxonomy will be based on occupational data discriminating between two different types and two levels of labour skills. It is assumed that the actual use of certain skills reflects corresponding technological constraints and market opportunities.

The data, which have recently been published by the OECD (1998), are available at the 2-digit level of ISIC Rev. 2 and distinguish four broad types of occupations, for which shares in total employment can be calculated: (i) *white-collar high-skill* (legislators, senior officials and managers; professionals, technicians and associated professionals); (ii) *white-collar low-skill* (clerks, service workers, shop & sales workers); (iii) *blue-collar high-skill* (skilled agricultural and fishery workers, craft & related trade workers); and finally (iv) *blue-collar low-skill* (plant & machinery operators and assemblers, elementary occupations). The shares in total employment of blue-collar high-skill and white-collar high-skill were used to maintain a concept of orthonormal space and a linear independence of the respective vectors of the variables. This reflects a conceptualisation of two linearly independent dimensions of blue- versus white-collar occupations, within which the individual scores for each industry illustrate the respective requirements for skilled labour. Since the number of available observations was much lower than in the previous case, the clustering process was executed in a simple one-stage algorithm. In order to maintain the linear independence of the basis vectors, only the shares of high-skilled white-collar and high-skilled blue-collar workers were used as discriminatory variables.

The overall clustering algorithm does not work equally as well as in the prior case of typical factor input combinations. As a consequence, the boundaries are more difficult to draw and `high-skill´ industries are mainly defined by outlying cases. evertheless, the most pronounced pattern was revealed by the combination of average linkages within groups and the simple Euclidean distance for any pair of industries i and j over k-variables:

(3) $$e_{ij} = \sqrt{\sum_{k=1}^{p} (x_{ik} - x_{jk})^2} \qquad 0 \le e_{ij} < \infty$$

The overall patterns in Figure 8 primarily reflect the distinction between industries with relatively higher shares of blue-collar workers (from the top of the dendrogram down to `rubber & plastic products´) and those with a majority of white-collar workers (from pharmaceuticals down to the bottom of the dendrogram). evertheless, in combination with Table 6, three distinct types of industries were created according to their overall skill requirements: In short, the so-called *`high skill´ industries* include non-electrical machinery among the more typical blue-collar industries, and pharmaceuticals, computers & office machinery, as well as aircraft, among the more typical white-collar industries. To a certain extent, they are all outlying cases, placed at the outer fringes of their respective clusters. In contrast, the final grouping of particularly `low skilled´ industries is represented by a bloc of observations, characterised by rather similar occupational structures with particularly low shares of white-collar high-skills and mean to low shares of blue-collar high-skills. All the remaining cases were labelled `medium skilled´, belonging to the groups of either typical blue- or white-collar industries.[8]

[8] Considering the unsatisfactory pattern in Figure 8 and the smaller number of industrial sectors, a simple cut-off procedure, which isolates only those industries with extraordinarily high shares of skilled labour, might be a reasonable alternative to the more complex clustering algorithm. In order to test for the general robustness of the final classification, two cut-off lines have been applied in an experimental setting: First, all industries with below-average shares in the total of white plus blue-collar skilled labour were cancelled. Secondly, among the remaining industries, only those with above average shares in white-collar skilled labour were finally labelled as being particularly skill intensive. Thus, particular skill intensive industries are defined by above-average shares in both white-collar high-skilled labour and total employment of high-skilled labour. In contrast to white-collar high-skilled labour, above-average shares in blue-collar high-skilled labour alone have not sufficed for qualification to this grouping. The intersection of both sets isolates five ISIC 2-digit groupings: air- and spacecraft, pharmaceuticals, computers & office machinery, precision instruments, and non electric machinery. Thus the only difference to our classification above is the inclusion/omission of precision instruments among the set of particularly high skilled industries. In addition, it must be mentioned that the built-in bias of this particular cut-off rules in favour of white-collar as opposed to blue-collar labour and has caused the following industries (with above average shares in blue-collar high-skilled labour, but with the total of skilled labour below average shares in white-collar skilled labour) not to be labelled as

Table 6: Average shares in total employment

SIC_Code	wc_hs	wc_lc	bc_hs	bc_ls
Food, drink & tobacco	14.18	16.64	38.96	29.94
Textile, footwear & leather	13.02	10.70	37.66	38.36
Wood, cork & furniture	12.99	9.85	45.00	31.98
Paper, printing & publishing	25.77	18.13	31.26	24.66
Petroleum refineries	35.55	16.18	19.69	28.23
Basic & other chemicals	33.38	18.96	16.34	30.88
Pharmaceuticals	46.13	20.67	11.42	21.49
Rubber & plastic products	18.91	12.58	17.64	50.42
Stone, clay & glass	17.14	11.94	35.50	35.18
Ferrous metals	19.25	10.53	33.75	36.17
Non ferrous metals	17.86	11.77	30.50	39.22
Other basic metals	17.08	10.91	33.44	38.57
Fabricated metal products	17.06	11.41	45.35	25.77
Non electrical machinery	25.66	13.39	40.27	20.31
Other electrical equipment	29.90	13.14	27.24	29.30
Computers & office equipment	51.94	16.66	18.70	12.58
Electronic equipment	33.83	14.24	23.09	28.04
Instruments	31.64	16.14	29.82	22.08
Motor vehicles	19.45	9.95	37.41	32.67
Shipbuilding	23.96	10.19	49.43	16.19
Other transport	19.38	12.06	38.57	29.65
Aircraft	38.71	13.33	32.62	15.21
Other manufacturing	19.14	15.23	39.77	25.34

Average shares in total employment for the latest year available: Australia (1991), Canada (1991), Finland (1990), France (1990), Western Germany (1990), Italy (1991), apan (1990), ew ealand (1996), nited Kingdom (1991), nited States (1994).

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particularly skill intensive: Wood, cork & furniture, fabricated metal products, other manufacturing, other transport, shipbuilding.

Figure 8: Manufacturing industries grouped according to similarities in labour skills

```
* * * * * * H I E R A R C H I C A L   C L U S T E R   A N A L Y S I S * * * * * *

Dendrogram using Average Linkage (Within Group) and Euclidean Distance
                                     Rescaled Distance Cluster Combine
          C A S E            0         5        10        15        20        25
  Label                          +---------+---------+---------+---------+---------+
  Motor vehicles           Med/bc -+
  Other transport          Med/bc -+-------+
  Other manufacturing      Med/bc -+       +-----+
  Non electr. machinery    High   ---------+     I
  Food, drink & tobacco    Low    -+---------+   +---+
  Textile, footwear        Low    -+         I   I   I
  Stone, clay & glass      Low    ---+       +---+   I
  Other basic metals       Low    ---+-+     I       +-+
  Ferrous metals           Low    ---+ +-----+       I I
  Non ferrous metals       Low    -----+             I +-----+
  Wood, cork & furniture   Med/bc ---------+---------+ I     I
  Fabricated metal         Med/bc ---------+           I     +---------------------+
  Shipbuilding             Med/bc ---------------------+     I                     I
  Rubber, plastic prod.    Low    ---------------------------+                     I
  Pharmaceuticals          High   -------------------------+-------------+         I
  Computer, office machin. High   -------------------------+             I         I
  Petroleum refineries     Med/wc -------+---+                           +---------+
  Electronic equipment     Med/wc -------+   +-------------+             I
  Basic & other chemicals  Med/wc -----------+             I             I
  Other electrical equip.  Med/wc -----+-----+             +-------------+
  Precision instruments    Med/wc -----+     +-------+     I
  Paper, printing & publ.  Med/wc -----------+       +-----+
  Aircraft                 High   -------------------+
```

Source: Peneder, 1999.

Figure 9: Shares in total employment: White-collar high-skilled

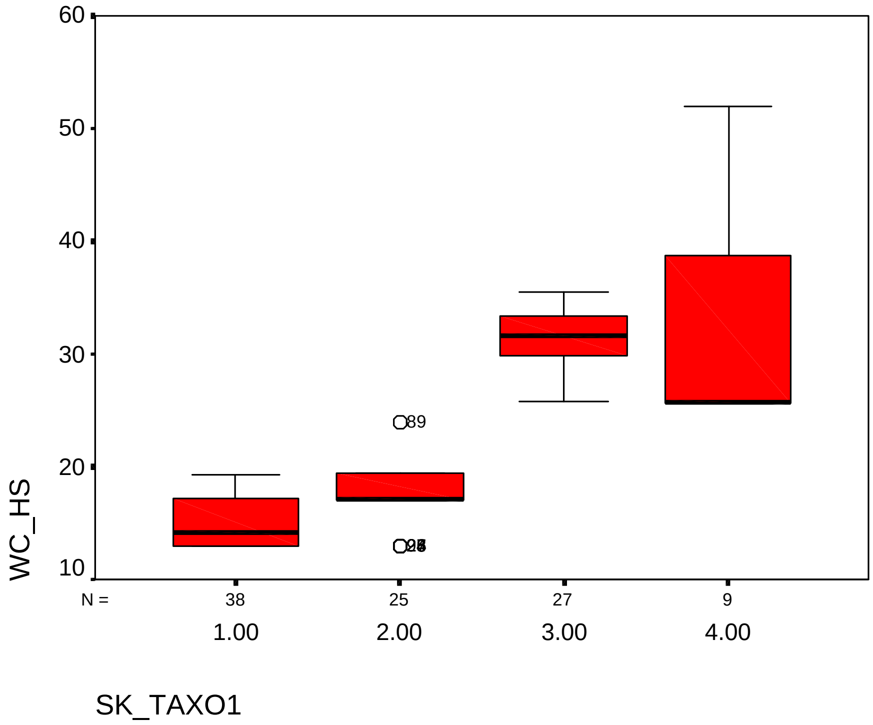
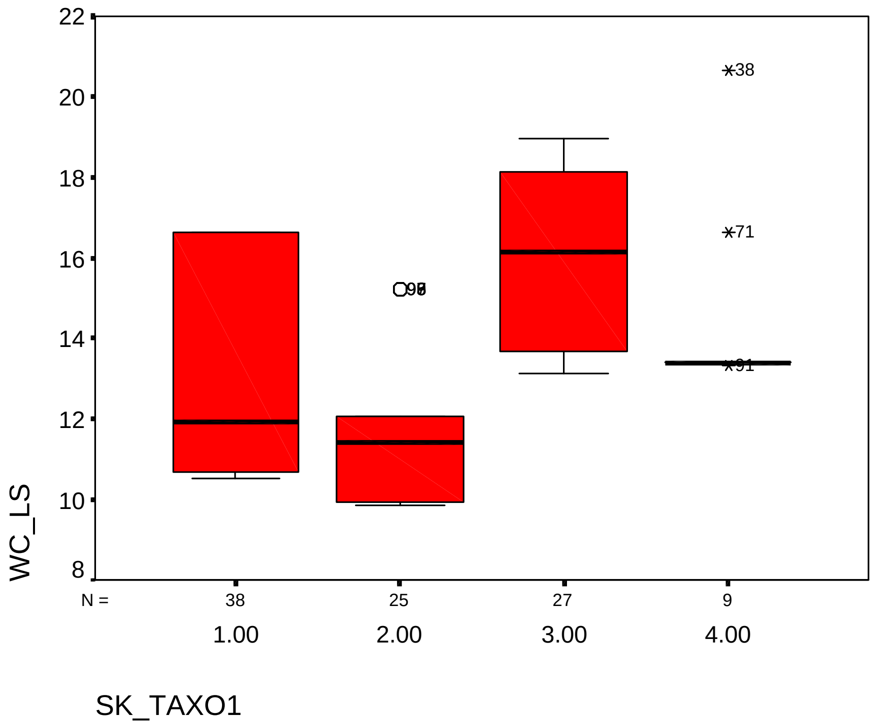


Figure 10: Shares in total employment: White-collar low-skilled



B: 1.. low-skilled; 2.. medium-skilled blue-collar industries; 3.. medium-skilled white-collar industries; 4.. high-skilled industries

Figure 11: Shares in total employment: Blue-collar high-skilled

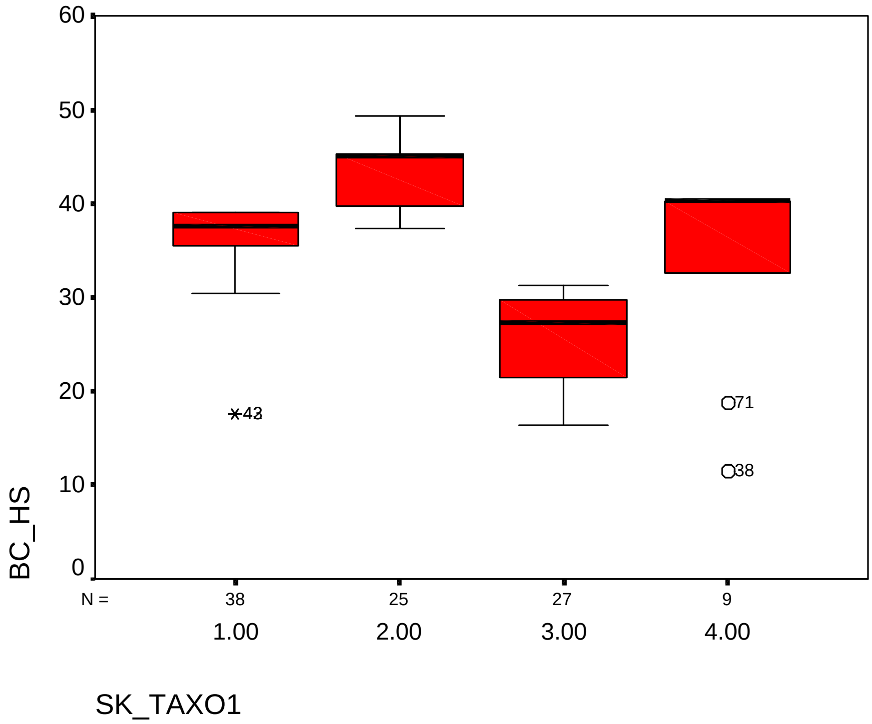
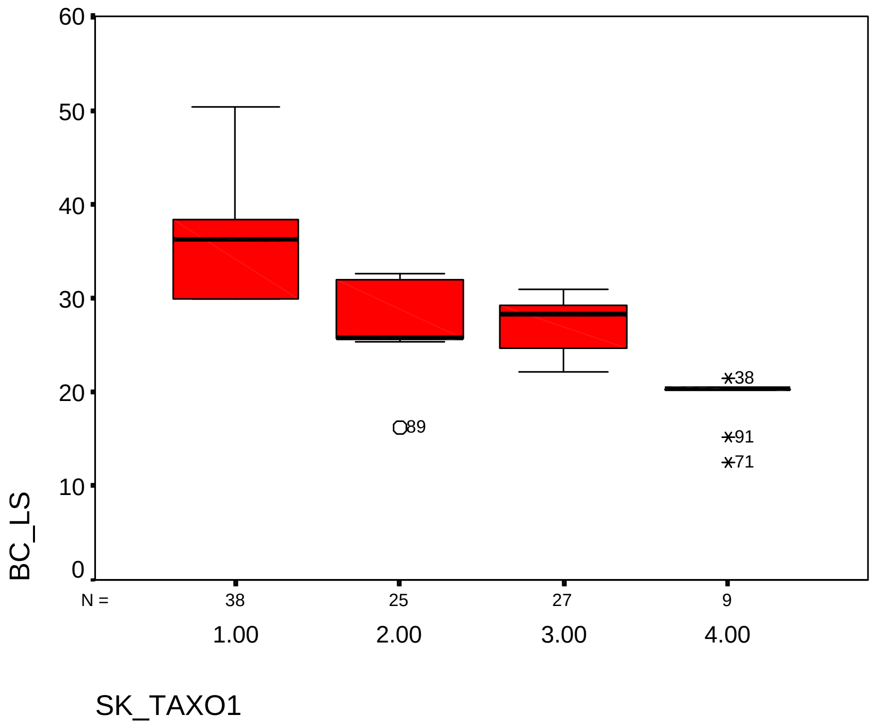


Figure 12: Shares in total employment: Blue-collar low-skilled



B: 1.. low-skilled; 2.. medium-skilled blue-collar industries; 3.. medium-skilled white-collar industries; 4.. high-skilled industries

6. On the interaction between intangible investments and human resources

In the new taxonomy presented in Section 3, the underlying concept of the firm was based on a broad notion of the production function, focusing on factor inputs to the generation of revenues rather than on pure physical output. This approach brought into perspective expenditures on R&D and advertising as intangible investments, intended to raise the consumer s willingness to pay for the specific output of the firm. In contrast, the second taxonomy, presented in Section 5.1 was purely based on human resources, focusing on two different kinds and two different levels of labour skills. In the respective statistical cluster analysis, both classifications had to be treated separately, enabling to formulate a reasonable concept for measuring similarities or differences between industries. Otherwise, a reasonable assumption of orthonormal space would not have been possible, and correlations between the input and skill variables would have introduced major distortions.

The purpose of this section is to investigate whether and to what extent these two different analytic layers and the respective taxonomies interlock. The interpretative framework starts with the assumption that human resources and factor inputs form two different layers in the \`anatomy´ of the firm. This corresponds to the resource based view of the firm, which has become increasingly popular in business economics and corporate strategy. At its very origin, Edith Penrose introduced an essential distinction, which is also relevant to this work:

> Strictly speaking, it is never *resources* themselves that are the inputs in the production process, but only the *services* that the resources can render. .. The important distinction.. lies in the fact that resources consist of a bundle of potential services and can for the most part, be defined independently of their use, while services cannot be so defined, the very word \`service´ implying a function, an activity. As we shall see, it is largely in this distinction that we find the source of the uniqueness of each individual firm. (Penrose, 1959, p. 25)

Table 7: The WIFO taxonomy of manufacturing industries

ACE	Industry	skill type	share in value added capital	labour	/net turnover r&d	in advertising
Mainstream manufacturing (MM)			**6.28**	**37.83**	**2.17**	**2.35**
1730	Finishing of textiles	LOW	6.56	40.70		
1770	Knitted and crocheted articles	LOW	6.00	43.49	1.98	2.89
1750	Other textiles	LOW	7.30	37.22	1.73	1.14
1760	Knitted and crocheted fabrics	LOW	8.64	42.41	1.98	2.92
2120	Articles of paper and paperboard	MED/ WC	6.69	36.01	3.40	3.01
2430	Paints, coatings, printing ink	MED/ WC	3.88	24.25	2.66	2.69
2510	Rubber products	LOW	6.81	38.67	2.54	2.03
2520	Plastic products	LOW	8.86	37.90	2.01	2.98
2610	Glass and glass products	LOW	8.84	35.62	2.55	3.37
2660	Articles of concret, plaster and cement	LOW	5.94	41.45	1.21	2.05
2680	Other non-metallic mineral products	LOW	6.41	30.93	1.89	1.82
2720	Tubes	LOW	7.40	41.68	2.04	2.01
2870	Other fabricated metal products	MED/ BC	6.07	43.31	1.44	3.03
2910	Machinery for production, use of mech. power	HIGH	6.22	39.77	2.30	2.57
2920	Other general purpose machinery	HIGH	5.21	43.60	2.01	1.60
2930	Agricultural and forestry machinery	HIGH	4.02	30.41	3.35	1.12
2950	Other special purpose machinery	HIGH	5.33	45.33	2.49	2.68
2960	Weapons and ammunition	HIGH	6.14	44.11	1.70	2.08
2970	Domestic appliances n. e. c.	MED/ WC	5.78	31.46	1.51	3.11
3110	Electric motors, generators and transformers	MED/ WC	5.30	41.06	2.65	1.36
3130	Isolated wire and cable	MED/ WC	6.62	35.18	2.29	2.11
3140	Accumulators, primary cells and primary batteries	MED/ WC	6.89	32.24	2.29	2.11
3150	Lighting equipment and electric lamps	MED/ WC	4.15	35.39	2.29	2.11
3540	Motorcycles and bicycles	MED/ BC	5.66	36.22	2.06	2.16
3550	Other transport equipment n. e. c.	MED/ BC	6.32	37.21	1.82	3.37
Labour intensive industries (LI)			**5.00**	**44.75**	**1.44**	**3.30**
1720	Textile weaving	LOW	9.33	45.97	0.69	4.79
1740	Made-up textile articles	LOW	4.59	44.02	1.60	3.16
1810	Leather clothes	LOW	0.83	43.18	2.70	3.40
1820	Other wearing apparel and accessories	LOW	2.17	40.81	1.45	3.86
1830	Dressing and dyeing of fur; articles of fur	LOW	3.23	37.68	3.96	2.95
2010	Sawmilling, planing and impregnation of wood	MED/ BC	7.02	39.97	0.19	3.57
2020	Panels and boards of wood	MED/ BC	6.30	39.01	0.69	4.37
2030	Builders carpentry and joinery	MED/ BC	4.08	47.04	0.67	3.23
2040	Wooden containers	MED/ BC	4.91	48.18	1.06	3.57
2050	Other products of wood; articles of cork, etc.	MED/ BC	3.37	40.78	2.70	3.11
2620	Ceramic goods	LOW	5.60	41.80	1.04	4.45
2640	Bricks, tiles and construction products	LOW	7.35	44.02	0.22	2.38
2670	Cutting, shaping, finishing of stone	LOW	5.18	46.89	1.10	2.74
2810	Structural metal products	MED/ BC	3.63	46.73	0.44	1.57
2830	Steam generators	MED/ BC	4.53	47.23	0.92	0.94
2840	Forging, pressing, stamping and roll forming of metal	MED/ BC	6.12	47.07	1.59	1.77
2750	Casting of metals	LOW	6.84	50.63	0.78	3.08
2850	Treatment and coating of metals	MED/ BC	6.00	44.67	2.60	4.62
2940	Machine-tools	HIGH	4.55	43.38	2.31	3.27
3160	Electrical equipment n. e. c.	MED/ WC	5.58	41.55	2.92	5.66
3420	Bodies for motor vehicles, trailers	MED/BC	9.31	52.54	0.70	2.53
3510	Ships and boats	HIGH	2.90	55.25	0.97	3.11
3520	Railway locomotives and rolling stock	MED/ BC	4.88	43.74	1.48	3.10
3610	Furniture	MED/ BC	3.94	45.30	1.32	4.62
3620	ewellery and related articles	LOW	2.72	41.22	1.79	2.77

B: MED/BC.. classified as `medium-skilled blue-collar industries´; MED/WC.. `medium-skilled white-collar´ industries.

Source: DEBA, COMPET, own calculations.

Table 7: The WIFO taxonomy of manufacturing industries (continued)

			share in value added /net turnover			in
ACE	Industry	skill type	capital	labour	r&d	advertising
Capital intensive industries (CI)			14.01	33.43	1.46	1.64
1710	Textile fibres	LOW	12.36	44.98	1.60	2.98
2110	Pulp, paper and paperboard	MED/ WC	21.28	30.43	1.05	1.91
2310	Coke oven products	MED/ WC	13.74	38.98	1.11	1.38
2320	Refined petroleum products	MED/ WC	25.73	16.85	0.68	1.38
2410	Basic chemicals	MED/ WC	14.33	21.52	3.55	2.49
2470	Man-made fibres	MED/ WC	12.94	28.83	3.15	1.14
2630	Ceramic tiles and flags	LOW	10.65	38.49	0.22	2.38
2650	Cement, lime and plaster	LOW	10.53	27.29	0.54	2.74
2710	Basic iron and steel, ferro-alloys (ECSC)	LOW	13.71	39.01	1.10	1.19
2730	Other first processing of iron and steel	LOW	10.41	36.17	0.88	0.18
2740	Basic precious and non-ferrous metals	LOW	11.13	35.31	1.04	0.67
3430	Parts and accessories for motor vehicles	MED/ BC	11.33	43.29	2.62	1.28
Marketing driven industries (MDI)			5.11	30.15	1.26	7.58
1510	Meat products	LOW	6.36	36.33	0.28	5.86
1520	Fish and fish products	LOW	7.13	33.19	1.00	7.23
1530	Fruits and vegetables	LOW	6.75	21.91	0.78	7.30
1540	Vegetable and animal oils and fats	LOW	8.55	18.93	0.15	7.09
1550	Dairy products; ice cream	LOW	6.27	24.82	1.67	5.46
1560	Grain mill products and starches	LOW	7.18	14.47	0.94	8.72
1570	Prepared animal feeds	LOW	5.09	18.28	0.94	8.72
1580	Other food products	LOW	5.29	22.39	0.65	6.93
1590	Beverages	LOW	5.88	18.40	0.76	6.47
1600	Tobacco products	LOW	1.58	6.33	0.47	7.61
1910	Tanning and dressing of leather	LOW	5.16	41.86	0.92	6.62
1920	Luggage, handbags, saddlery and harness	LOW	2.06	39.49	0.92	6.62
1930	Footwear	LOW	2.37	39.53	0.92	6.62
2210	Publishing	MED/ WC	3.93	31.10	3.16	6.41
2220	Printing	MED/ WC	5.60	40.59	1.36	6.22
2230	Reproduction of recorded media	MED/ WC	9.99	27.83	1.58	6.64
2450	Detergents, cleaning and polishing, perfumes	MED/ WC	4.61	14.58	2.78	9.45
2820	Tanks, reservoirs, central heating radiators and boilers	MED/ BC	4.14	44.11	0.40	5.15
2860	Cutlery, tools and general hardware	MED/BC	5.53	45.06	1.88	10.49
3350	Watches and clocks	MED/ WC	3.03	37.70	0.99	9.33
3630	Musical instruments	LOW	2.36	45.25	0.87	7.33
3640	Sports goods	LOW	4.20	31.89	1.70	5.73
3650	Games and toys	LOW	4.96	31.72	2.95	14.48
3660	Miscellaneous manufacturing n. e. c.	LOW	4.54	37.90	2.13	9.39
Technology driven industries (TDI)			6.91	31.21	5.85	2.64
2420	Pesticides, other agro-chemical products	MED/ WC	7.63	11.87	1.21	2.73
2440	Pharmaceuticals	HIGH	7.19	16.35	12.97	5.93
2460	Other chemical products	MED/ WC	7.71	24.01	3.41	2.98
3000	Office machinery and computers	HIGH	7.07	31.63	6.91	1.49
3120	Electricity distribution and control apparatus	MED/ WC	4.91	37.25	4.63	1.68
3210	Electronic valves and tubes, other electronic comp.	MED/ WC	12.16	33.30	7.12	2.20
3220	TV, and radio transmitters, apparatus for line telephony	MED/ WC	5.64	33.93	9.15	1.52
3230	TV, radio and recording apparatus	MED/ WC	10.42	30.88	5.54	3.48
3310	Medical equipment	MED/ WC	5.58	32.73	7.15	1.41
3320	Instruments for measuring, checking, testing, navigating	MED/ WC	4.23	43.82	5.30	2.61
3330	Industrial process control equipment	MED/ WC	4.95	43.19	4.02	0.83
3340	Optical instruments and photographic equipment	MED/ WC	6.35	26.69	6.09	4.27
3410	Motor vehicles	MED/ BC	7.86	25.78	4.31	2.03
3530	Aircraft and spacecraft	HIGH	5.06	45.56	4.14	3.74

B: MED/BC.. classified as `medium-skilled blue-collar industries´; MED/WC.. `medium-skilled white-collar´ industries.

Source: DEBA, COMPET, own calculations.

Thus, the term `resources´ defines a distinct analytic layer beneath the actual inputs used by the firm during the course of its economic activities. Any inputs must be drawn as specific services from the pool of resources, which are either externally or internally available to the firm. Thus for each of the four dimensions of factor inputs, it is in principle possible to define a corresponding resource base. This refers to tangible assets such as e.g. the physical stocks of plant and machinery, as well as intangible knowledge-based resources, as e.g. the basic technological and marketing know-how for launching a new research programme or advertising campaign. A part of these knowledge-based resources might be purchased on external markets - specialised consulting services, for example. Other parts can be generated by the accumulation of past experiences within the firm. But finally, these knowledge-based resources are also dependent on the available qualifications of the people employed. For lack of appropriate data on the other dimensions, it is only this last aspect, which can be integrated into our empirical setting. Despite their contributions to the general stock of accumulated knowledge, any investments e.g. in advertising and R&D are exclusively attributed to the analytic layer of actual service inputs. Any positive feedback on the own knowledge base are thought of as indirect effects, stemming from the accumulation of past experiences.

Investigating the relationship between labour skills and typical factor input combinations, no clear causal structure can be specified. As, for example, research activities might be dependent on the availability of skilled labour, the causal link can also be precisely the reverse in the sense that the demand for skilled labour positively depends on corresponding investments in R&D. Therefore, the true question of interest is, whether the different types and different degrees of human resources, as well as intangible investments, can be characterised by any statistically significant complementary relationships. Thus, we are not concerned with any detailed specification of functional forms and causal links, but concentrate only on the observable patterns of co-movement. This task bears some similarity to recent theoretical (Milgrom-Roberts, 1990, 1995) and empirical (Ichniowski-Shaw-Prennushi) research on firm organisation and the complementarity of different work practices.

Beginning with a simple correlation analysis, the following relationships between the continuous variables on factor inputs and occupations appeared to be significant at the

5 level: Capital intensity is negatively correlated with blue-collar high-skills, whereas labour intensity is negatively correlated with both types of white-collar occupations and positively correlated with blue-collar low-skills (+0.480). Advertising outlays are positively correlated with white-collar high-skills (+0.310), but negatively so with white-collar high-skills. Among the four input variables, intangible investments in R&D are most strongly related to the dimension of human resources, with significant correlations to all different types of occupations. Strong positive correlations occur between both types of white-collar labour, and are particularly strong for high-skills (+0.678) and somewhat less so for low-skills (+0.324). In contrast, research expenditures are negatively correlated to shares of blue-collar workers in total employment.

Similarly, non-parametric tests on differences in the employment shares of various types of occupations across industries, classified according to their typical factor input combinations, indicate strong and significant relationships between intangible investments and human resources (Table 8):

- Technology driven industries characterised by typically high intangible investments in research & development significantly show the lowest shares in both blue-collar low- *and* high-skill labour, but the highest shares in white-collar low- *and* high-skill labour.

- In contrast, for marketing driven industries, the shares of blue-collar low-skill labour are significantly lower and those of blue-collar high-skill labour are higher than in most other groupings. The reverse applies with regard to white-collar occupations, where low-skills have high shares and high-skills hold low shares.

As far as the other groupings are concerned, the most pronounced observation concerns labour intensive industries, which typically employ many more blue-collar than white-collar workers of both types. In contrast, mainstream manufacturing and capital intensive industries each reveal a mixed balance.

Table 8:   on parametric tests for significant differences in labour skills

Shares in total employment	number of industries	unweighted mean	mean rank	Industry type	Mann-Whitney *U* test / Kolmogorov-Smirnov *Z* test				
					MM	LI	CI	MDI	RDI
Blue collar/ low skill	25	31.39	52	MM	-	-	-	-	*
Median Test: ***	25	31.37	59	LI	-	-	-	***	***
Kruskal-Wallis *H* test: ***	11	33.42	67	CI	-	-	-	***	**
	24	28.93	44	MDI	-	**	***	-	**
	14	24.67	28	TDI	**	***	***	*	-
					MM	LI	CI	MDI	RDI
White collar/ low skill	25	12.78	47	MM	-	***	-	***	***
Median Test: ***	25	11.16	25	LI	***	-	-	***	***
Kruskal-Wallis *H* test: ***	11	13.6	48	CI	-	*	-	-	**
	24	15.49	69	MDI	***	***	-	-	-
	14	15.64	70	TDI	***	***	-	-	-
					MM	LI	CI	MDI	RDI
Blue collar/ high skill	25	34.49	46	MM	-	**	-	**	***
Median Test: ***	25	40.49	69	LI	***	-	***	**	***
Kruskal-Wallis *H* test: ***	11	29.79	30	CI	-	***	-	***	**
	24	37.18	62	MDI	*	-	***	-	***
	14	24.9	18	TDI	***	***	*	***	-
					MM	LI	CI	MDI	RDI
White collar/ high skill	25	22.13	54	MM	-	**	-	**	***
Median Test: ***	25	16.69	30	LI	***	-	**	-	***
Kruskal-Wallis *H* test: ***	11	22.84	60	CI	-	***	-	**	**
	24	18.08	40	MDI	**	-	**	-	***
	14	34.35	88	TDI	***	***	***	***	-

NB: MM.. mainstream manufacturing; LI.. labour intensive..; CI.. capital intensive..; MDI..marketing driven..; TDI.. technology driven industries

*** significant at the 1% level

** significant at the 5% level

* significant at the 10% level

Finally, the twofold application of multinomial logit regressions is used in a further exploration of the presumed complementary relationship between the two distinct analytic layers. For lack of a more profound specification of the causal model, a simple regression was calculated first, taking taxonomy I as a dependent variable and the respective shares in employment of white-collar low-, white-collar high- and blue-collar high-skilled labour as independent variables. Mainstream manufacturing is used as the comparison group. The underlying hypothesis is that the final classification of a particular industry within either research-, advertising-, capital- or labour-intensive production can be predicted, at least in part, on the basis of its known human resource base. Assuming complementarity between labour skills and intangible inputs to production, the most simple prediction would suggest positive coefficients for both types of high-skilled labour and negative coefficients for both types of low-skilled labour for marketing and technology driven industries, and the reverse for labour intensive industries. o specific hypothesis on different labour requirements relative to the comparison group seems obvious for capital intensive industries.

Since we are already familiar with prior test statistics, we must expect that these simple predictions will not be confirmed in their entirety. Corresponding to our lack of any causal hypothesis, an industry s probability of being particularly *capital intensive* cannot be related to any of the occupational categories. In contrast, more shares of blue-collar high-skill labour e.g., have a significant impact on the probability of being grouped among *labour intensive industries*. Similarly, the only positive and strong effect on the probability of belonging to *marketing driven industries* depends on the share of low-skill white-collar workers, whereas higher shares in white-collar high-skill labour significantly decrease this probability. Finally, the regression analysis nevertheless confirms at least one of the prior predictions: A larger share of high-skilled white-collar labour has a significant positive impact on the probability of belonging to the *technology driven industries*. With a Likelihood-Ratio-Index (Pseudo R^2) of 0.37 and 61 scores (out of 99 cases, each offering 5 alternative realisations) correctly predicted (Table 10), the model generally supports the claim that the two dimensions of factor inputs and intangible investments on the one hand, and human resources on the other, are strongly interlocked.

Table 9: Skill requirements across the taxonomy of typical input combinations

Multinomial regression		umber of obs	99	
		LR chi2(12)	115.61	
		Prob chi2		0.0000
Log likelihood	-96.571596	Pseudo R2	0.3744	

taxo1	Coef.	Std. Err.	z	P z	95	Conf. Interval
Labour intensive industries						
wc hs	-.0817512	.0906266	-0.902	0.367	-.2593761	.0958737
wc ls l	-.0868515	.2837832	-0.306	0.760	-.6430564	.4693533
bc hs	.1638977	.0706878	2.319	0.020	.0253521	.3024434
cons	-3.637895	4.20244	-0.866	0.387	-11.87453	4.598736
Capital intensive industries						
wc hs	-.0807778	.0887795	-0.910	0.363	-.2547824	.0932267
wc ls	.1498079	.2351583	0.637	0.524	-.311094	.6107097
bc hs	-.0640185	.061964	-1.033	0.302	-.1854657	.0574287
cons	1.048763	3.942933	0.266	0.790	-6.679244	8.776769
Advertising intensive industries						
wc hs	-.2959877	.1182767	-2.503	0.012	-.5278058	-.0641695
wc ls	.9690193	.2474688	3.916	0.000	.4839895	1.454049
bc hs	.1136329	.081046	1.402	0.161	-.0452143	.2724801
cons	-11.44318	4.871834	-2.349	0.019	-20.9918	-.894563
Research intensive industries						
wc hs	.3651216	.1685354	2.166	0.030	.0347982	.695445
wc ls	-.0270111	.2520659	-0.107	0.915	-.5210512	.467029
bc hs	.0592727	.0943038	0.629	0.530	-.1255593	.441048
cons	-12.39113	8.022011	-1.545	0.122	-28.11399	.31717

(Outcome taxo1 1 `mainstream manufacturing´ is the comparison group)

Table 10: Predicting taxonomy I (factor inputs) according to labour skills

fai_taxo	MM	LI	CI	MDI	TDI	Total
MM	14	7	2	1	1	25
LI	6	18	0	1	0	25
CI	5	2	0	1	3	11
MDI	0	5	0	17	2	24
TDI	1	1	0	0	12	14
Total	26	33	2	20	18	99

Since we tend to imagine a kind of interdependent causation and do not think in terms of a unidimensional causal specification, it might be reasonable to test also for the analogous hypothesis that the relative size of factor inputs has a significant impact on the overall level of required skills. Certainly, this does not eliminate the problem posed by the endogeneity of the variables. evertheless it does provide an additional test of whether and how intangible investments and human resources actually interlock. Compared to the grouping of industries characterised by particularly high shares of low-skilled (mostly blue-collar) workers, the results indicate the positive impact of higher labour intensities on the probability of belonging to the grouping of medium-skilled blue-collar industries. Besides this significant, albeit weak effect, research expenditure is the only variable which exerts a meaningful impact on the demand for particular types of occupations. Being highly significant, higher intangible investments in R&D have a positive effect on the probability of belonging either to the grouping of high-skilled industries or white-collar medium-skilled industries. Again, with a value of 0.29, the Likelihood-Ratio-Index is satisfactory (in multinomial logit regressions, values between 0.2 and 0.4 are generally considered as indicative of a good fit). Based on the data for typical factor intensities, the model generates 57 correct predictions from 98 cases (each offering 4 alternative realisations).

In short, this final section proves the existence of strong empirical regularities between the distinct analytic levels of human resources on the one hand, and intangible investments on the other. The interpretative framework follows the resource-based view of the firm in its distinction of general resources available to the firm, and the specific bundles of services, which can be drawn from it. Seen from this perspective, human knowledge-based resources form a separeate analytic layer, which is nevertheless interlocked with the observed variables on factor inputs the actual stream of long term investments in such areas as physical capital, advertising or R&D included. The overall results confirm a particularly strong relationship between intangible investments in R&D and the underlying type of human knowledge-based resources, which emphasise the complementary nature of white-collar high-skill, and to a somewhat lesser degree, also white-collar low-skill occupations. In contrast, intangible investments in advertising and brand creation cannot be associated with any significant complementary relationship to either of the two types of high-skilled labour. On the contrary, their overall pattern exhibits a strong complementarity with respect to white-collar low skill occupations.

Table 11: Skill requirements and factor inputs

Multinomial regression umber of obs 98
LR chi2(12) 72.36
Prob chi2 0.0000
Log likelihood -90.307608 Pseudo R2 0.2860

sk taxo1	Coef.	Std. Err.	z	P z	95 Conf.	Interval
2						
capital	-.1019743	.1254102	-0.813	0.416	-.3477736	.1438251
labour	.1351973	.0503797	2.684	0.007	.0364549	.2339397
research	.5271387	.3576197	1.474	0.140	-.173783	1.22806
advertis	.1557607	.1319321	1.181	0.238	-.1028215	.4143428
cons	-6.560336	2.808587	-2.336	0.020	-12.06506	-1.055607
3						
capital	.1134072	.0849305	1.335	0.182	-.0530534	.2798678
labour	-.0503174	.0376055	-1.338	0.181	-.1240228	.023388
research	1.453429	.3686871	3.942	0.000	.7308155	2.176042
advertis	-.0313948	.1431092	-0.219	0.826	-.3118837	.2490941
cons	-2.144657	2.093841	-1.024	0.306	-6.248509	1.959195
4						
capital	-.0964735	.1910588	-0.505	0.614	-.470942	.2779949
labour	.0691016	.0770337	0.897	0.370	-.0818818	.2200849
research	1.723546	.4048295	4.257	0.000	.9300949	2.516997
advertis	-.1035471	.2489604	-0.416	0.677	-.5915006	.3844063
cons	-6.905993	4.135498	-1.670	0.095	-15.01142	1.199435

(Outcome sk taxo1 1 is the comparison group)

Table 12: Predicting taxonomy II (labour skills) by means of factor input combinations

skill_taxo	Low	Med/bc	Med/wc	High skill	Total
Low skill	25	9	3	1	38
Med/bc	9	14	2	0	25
Med/wc	4	3	17	3	27
High skill	2	3	3	1	9
Total	40	29	25	5	99

7. Summary and outlook

This paper is centred around the following primary tasks: First of all, the analysis set out to test the hypothesis that the importance of intangible investments and specific skill requirements differs across industries. Any rejection of that hypothesis would imply that the question regarding the impact of intangible investments on competitive performance has no meaning at the industry level. As a consequence, analysis would have to be restricted to the firm level, with the easily predictable effect of cancelling most prospects for large scale international comparisons. The results from the statistical cluster analysis convincingly demonstrate that industries do indeed differ in their propensity to undertake intangible investments in advertising or R&D and that they do so in a remarkably systematic and pronounced way. The same applies to human resources, albeit in a less pronounced and clear-cut pattern.

Secondly, by means of statistical cluster techniques, two new taxonomies of manufacturing industries were created. The first one is based upon distinctions in an industry s typical factor input combinations and comprises data on labour inputs, capital investment, as well as intangible investments in advertising and R&D. In contrast, the second taxonomy focuses on the human resources dimension and is based upon the average shares of different types of occupations, distinguishing between blue- and white-collar, as well as high- and low-skill labour. Allowing serious problems due to the lack of internationally comparable data to be side-stepped, these taxonomies establish generally applicable instruments for future research at the industry level. The taxonomies have already been successfully applied in the European Competitiveness Report 1998 (European Communities, 1998).

Thirdly, in its final section, the analysis set out to test the hypothesis that the employment of high-skilled labour varies complementarily to intangible investments in advertising and R&D. The results of the correlation analysis, non parametric tests on the statistical significance of observable differences, as well as multinomial logit regressions, uniformly stressed the dependence of this relationship on the particular types of intangible investments and occupations. For example, no significant complementary relationship between high-skilled labour and advertising outlays could be found. On the contrary, advertising is revealed as having the most complementary relationship to the employment of white-collar low-skilled labour. But for intangible investments in research & development, a strong and highly significant complementarity to the employment of high skilled white-collar workers does exist, confirming our prior expectations in favour of this specific relationship.

Given these three main results, a profound and workable basis has been established for further investigation, according to the overall research plan. In the next, immediate step of the program, the analysis will focus on the question, *whether and to what extent intangible investments make a difference in overall economic performance*. In particular, the two new taxonomies will be applied in a test of whether the higher propensity to invest in intangibles, such as advertising and R&D, leads to a significant difference in productivity levels, wages, employment or growth, and the differentiability of products. First test calculations have already brought to surface a considerable number of such significant differences. These results are envisaged as establishing the basic rationale and foundation for the last step of the programme, focusing on international comparisons of relative specialisation patterns, again applying the two new industry classifications. The investigation will then turn to the third and final step of the analysis, examining whether and to what extent industrial structures differ in an *international comparison,* as they reflect variations in the typical propensity to make intangible investments.

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