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## Innovation strategies of firms: Identification, dynamics and intra-industry heterogeneity

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## Innovation strategies of firms – identification, dynamics and intra-industry heterogeneity

*Heinz Hollenstein*

### Abstract

The study aims at providing new evidence with respect to the still unresolved question, whether the innovation behaviour of firms reflects industry-specific characteristics (“technological regime approach”), or whether it is the outcome of firm-specific strategies to gaining a competitive edge (“strategic management view”). To this end, the author firstly identifies a set of innovation strategies (cluster analysis), whose adequacy he evaluates using the “economics of innovation” as reference. Secondly, the author investigates the dynamics of innovation strategies to get some insights into structural changes of the economy. Thirdly, he examines, based on a large number of 4-digit branches, the intra-industry heterogeneity of innovation strategies. Finally, the author analyses in a production function framework the relative importance of a company’s innovation strategy and its industry affiliation as determinants of firm performance. The third part of the paper tends to support the “strategic management view” (high intra-industry heterogeneity), while the final one is rather in line with the “technological regime approach” (industry affiliation is the more important factor determining firm performance). These opposite findings indicate that a company has a certain room of manoeuvre to choose an innovation strategy in line with its specific capabilities, but some structural characteristics at industry level restrict the strategic options.

**JEL** O30 O31 O32 O33

**Keywords** Innovation; firm-level taxonomy of innovation strategies; dynamics of innovation strategies; intra-industry heterogeneity of innovation behaviour; impact of firm strategies and industry affiliation on performance

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## 1 Introduction

Each firm pursues a specific innovation strategy with the objective to gaining a competitive advantage. To this end, the company draws on some unique, mostly complementary capabilities (technological, organisational, human and other resources). This view of the firm is a core concept of the “*strategic management literature*”, which is specified in several but effectively quite similar ways. To mention are primarily the “resource-based view of the firm” (Wernerfelt 1984), the “dynamic capability approach” (Teece et al. 1997; Teece 2010), or the concept of the “knowledge-based company” (Kogut and Zander 1993). Some other researchers emphasising the strategic behaviour of heterogeneous firms even find significant performance differences among sub-groups of a company (see, e.g., Rumelt 1991; McGahan et al. 1997).

In contrast, the “*technological regime approach*” (see, e.g., Nelson and Winter 1977, 1982; Dosi 1982, 1988; Winter 1984) asserts that innovation strategies of firms of the same industry are similar, as technological opportunities, sources of knowledge, appropriability conditions, cumulativeness of knowledge, the market environment, etc. do not much vary within an industry (or even a group of industries). This theoretical approach is reflected in the seminal contribution of Pavitt (1984), who distinguishes four types of innovation patterns, each of them representative for a number of industries (supplier dominated industries, scale intensive industries, specialised suppliers, science-based industries). Further (empirical) work refined this approach (e.g., Malerba and Orsenigo 1993, 1997; Breschi et al. 2000; Peneder 2010) and/or extended it to include service industries (see, e.g., Evangelista 2000; Miozzo and Soete 2001; Castellaci 2008).

Empirical work conducted at the firm level provides, among other things, information on the relationship between innovation strategies and industry affiliation. The results mostly challenge the technological regime approach, as they point to a substantial intra-industry heterogeneity of innovation modes (Cesaratto and Mangano 1993; Arvanitis and Hollenstein 2001; Hollenstein 2003; de Jong and Marsili 2006; Tiri et al. 2006; Jensen et al. 2007; Frenz and Lambert 2012; Srholec and Verspagen 2012; Chang and Chen 2016). However, as the large intra-industry variance of strategies observed in these papers throughout refers to the *2-digit NACE classification*, the evidence is not conclusive. Two-digit branches mostly cover a too wide array of economic activities (Archibugi 2001). Therefore, to effectively testing the heterogeneity hypothesis, it is necessary to use a more differentiated classification of industries, which allows an analysis based on *similar* economic activities. To our knowledge, Leiponen and Drejer (2007) is the only investigation of this type. This study confirms the heterogeneity hypothesis but its database is thin in terms of the number of industries included (see Section 5). It is thus premature to draw far-reaching conclusions. As we have at our disposal information for a very large number of industries (4-digit NACE classification), we are in a better position to provide evidence with regard to the appropriateness of the heterogeneity hypothesis.

Against this background, we empirically analyse for the entire business sector of the Swiss economy *four topics*, which refer to the issue on whether the innovation strategies of firms substantially vary within industries (heterogeneity hypothesis, reflecting the strategic management view), or whether

the firms of a specific industry pursue similar strategies (homogeneity hypothesis, standing for the technological regime approach). To the best of our knowledge, previous research rarely or inadequately dealt with these problems.

*Firstly*, as a preparatory step of the analysis of the intra-industry heterogeneity of innovation patterns, we identify *a set of innovation strategies of firms*. To this end, we perform a cluster analysis (which meanwhile is the standard approach in this matter), drawing on a large set of innovation indicators. In contrast to other studies, however, we evaluate the resulting clusters from an “external point of view”, that is, we characterise the clusters by use of a number of theory-based variables that we do not use in the preceding clustering process. This procedure allows to assessing whether we effectively may interpret the identified clusters as specific “modes of innovation” or “innovation strategies”. Moreover, as the analysis uses data from four waves of the “Swiss Innovation Survey” covering a period of ten years (1999 to 2008), the results should be less dependent from time-specific circumstances than it is the case in previous research that throughout rests on a single cross-section.

*Secondly*, we provide a descriptive analysis of the *dynamics of innovation strategies*. To this end, we seek to determine (a) to what extent firms adapt over time their innovation strategy by switching from the current to another cluster (innovation strategy), and (b) whether there are typical patterns of such shifts to a new strategy. As this investigation refers to a ten-year period, it may provide information on the structural change of innovation strategies of firms as well as the business sector as a whole. To the best of our knowledge, there is, to date, no large-scale empirical research dealing at the firm level with the dynamics of innovation strategies. This investigation, in addition to its value on its own, provides further evidence on whether the clusters previously identified effectively represent different innovation strategies.

*Thirdly*, we aim at identifying the extent of *intra-industry heterogeneity* of innovation strategies at the 4-digit industry level. To this end, we closely follow the approach of the only study performed at this high level of disaggregation (Leiponen and Drejer 2007). We are thus able to assess the results in a comparative perspective (Switzerland vs. Finland). As our analysis relies on a much larger number of 4-digit industries (see Section 5), we may provide more reliable evidence with respect to the discussion on whether innovation modes are specific to firms (strategic management concept), or largely are homogeneous within industries (technological regime approach).

*Finally*, we analyse econometrically the relationship between a firm’s *innovation strategy and performance*. The strategic management view would be superior if the impact on firm performance due to the choice of specific innovation strategies is larger than that attributed to industry affiliation. This analysis complements the research on the intra-industry heterogeneity of the firms’ innovation behaviour mentioned in the previous paragraph. To our knowledge, there are only four studies dealing with this topic applying econometric methods (Hollenstein 2003; Frenz and Lambert 2009, 2012; Sanchez 2014). As the theoretical basis of these analyses, with the exception of Hollenstein (2003), is not convincing – they neglect the productivity effect of the production factors such as physical, human and R&D capital –, we are able to extend significantly the existing knowledge.

The paper is organised as follows: The next section provides information on the dataset. In Section 3, we describe the methodology applied for identifying a number of “modes of innovation” (“innovation strategies”) at firm level, present the corresponding empirical results, and, finally, evaluate the adequacy of the innovation modes from a theoretical point of view. Section 4 deals with the dynamics of innovation strategies, that is, the frequency and direction of switches between innovation modes over time. Next, we analyse the intra-industry heterogeneity of innovation strategies at the 4-digit industry level. In Section 6, we present econometric estimates of the relationship between a firm’s innovation strategy and economic performance. Finally, we summarise and assess the main findings.

## 2 Data

The data we use in this study stem from the Swiss Innovation Survey conducted by the KOF Swiss Economic Institute (ETH Zurich) in the business sector every third year since 1990. The survey is based on a random sample of firms (5 or more employees) drawn from the official enterprise census, which is stratified by 29 industries and 3 industry-specific firm size classes (with full coverage of large companies). The survey yields information on a large number of innovation measures, on specific indicators useful to characterise a firm’s innovation strategy, and on variables to explain the level and intensity of innovation activities. Moreover, it provides data on some structural attributes of firms and their economic performance. A unit non-response analysis conducted for each survey based on a few innovation-related questions did not show any signs of a serious selectivity bias with respect to the basic sample.

For the present investigation, we use the data from four waves of the innovation survey conducted by use of an almost identical questionnaire (1999, 2002, 2005 and 2008).<sup>1</sup> As we analyse the firms’ modes of innovation, we confine the sample to innovative companies, meaning that we use information from 5645 (60%) out of the 9451 companies for which valid information is available. Firms are innovative if they generate product and/or process innovations in the year of the survey or the two preceding years. To a certain extent, we also account for non-technological innovations, as the definition of “innovation” used in the questionnaire, in several instances, is not technology-related. Among the indicators we use in this paper we may mention measures like “significance of innovations in economic terms”, “outlays for innovation-related training”, “expenditures for the introduction of innovative products on the market”, or “sales share of new or significantly improved products”. Nevertheless, the innovation survey does not *directly* ask for information on non-technological innovations, as it is the case in the well-known “Community Innovation Survey” (CIS).<sup>2</sup>

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<sup>1</sup> The questionnaire used in the four waves of the survey is available in German, French and Italian on [www.kof.ethz.ch/en/surveys/structural-surveys/kof-innovation-survey.html](http://www.kof.ethz.ch/en/surveys/structural-surveys/kof-innovation-survey.html).

<sup>2</sup> Only more recent waves of the KOF Innovation Survey provide this type of information. However, the questionnaire used from 2011 onwards is not comparable with that we sent to the firms up to 2008.

The dataset constitutes an unbalanced panel of four cross-sections as not all firms included in the total sample took part in each wave of the survey, and some of them did not generate innovations in each reference year. At least, the 5645 observations of the total sample are quite evenly distributed over the four cross-sections (24%, 27%, 26% and 23% of the sample), reflecting the fact that the response rate and the share of innovative firms do not much diverge among the four waves of the survey. Furthermore, we correct for *item* non-response by imputing missing values (“multiple imputation”; see Rubin 1987) to avoid a loss of observations that would introduce a bias to the final dataset. Altogether, the data is representative for the underlying sample. Table A.1 in the appendix shows the composition of the final sample by sector and industry.

### 3 Identification and interpretation of innovation modes

#### 3.1 Methodology

The analysis aims at identifying specific modes of innovation (innovation strategies) *at the firm level*. To this end, we use largely the method applied by Hollenstein (2003) in a cross-section study for *services* firms. We assume that a firm pursues only one type of innovation strategy. Since the data refer to the firm’s *main* economic activity, this assumption should not be too much a simplification.

For the present purpose, we apply a two-step procedure. In a *first step*, we perform a *cluster analysis* in order to group the firms into homogeneous categories with respect to fifteen indicators of innovation. These cover the input and the output side of the generation innovations, as well as the introduction of new products on the market and new processes in the firm. Two indicators are explicitly IT-related, which, quite surprisingly, is rarely the case in previous research. For the precise definition and the measurement of the fifteen variables, see Table 1. We do not conduct the cluster analysis *directly* to these variables. Instead, we start by synthesising the information contained in the individual measures into a small number of variables by means of a factor analysis. The resulting “*factors*” are uncorrelated standardised variables capturing the common information of the fifteen original variables. Then, we perform a non-hierarchical cluster analysis of these factors in order to group the firms in a set of categories (“*clusters*”), which are, with respect to the variables under investigation, as homogeneous as possible (small *within*-cluster variance), and, at the same time, as different as possible (large *between*-cluster variance).<sup>3</sup>

Table 1 (*about here*)

In a *second* step, we examine whether we effectively may interpret the clusters identified in the first step as different “modes of innovation”. To this end, we characterise the clusters in terms of three

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<sup>3</sup> The procedure involves partitioning the sample, allowing observations to move in and out of groups at different stages of clustering. At the beginning, more or less arbitrary group centres (“cluster seeds”) are chosen and individual observations allocated to the nearest one. Later on, an observation is moved to another group, if it proves to be closer to that group’s centre than to the centre of the initial group. This process, during which close groups are merged and distant ones split, is continued until stability is achieved with a predetermined number of clusters (see Manly 1986).

categories of variables: (a) the innovation indicators used in the clustering process, complemented by a set of measures that capture the direction of innovation efforts in more detail (“objectives of innovation”); (b) a series of important determinants of innovation activity, as postulated in the (empirical) innovation literature (see, e.g., the surveys of Cohen 1995, 2010), which pertain to the demand side (market prospects, intensity of competition, market concentration) and the supply side (technological/innovation opportunities, appropriability of knowledge, human resources) of the innovation process; (c) a set of variables characterising a firm’s knowledge network (intensity of use of various external sources of knowledge as well as significance of R&D contracts and of institutionalised R&D co-operation). According to the model formulated by Arvanitis and Hollenstein (1994), we also may interpret these indicators of a firm’s knowledge network as supply side determinants of innovation activity. Finally, we provide for each cluster information on firm size, firm age and the firms’ export orientation.

Most researchers seeking to identify innovation modes (for references see subsection 3.4) use at the clustering stage not only variables of category (a), i.e. innovation indicators, as we do, but include also variables of category (b) and/or (c). However, in so doing, they end up with only few (if any) variables they can use as “*external criteria*” (i.e., variables not included in clustering) for evaluating the plausibility of the innovation modes from an *independent point of view*. As emphasised in the statistical literature, an “external validation” of the clusters based on a *contextual assessment* (and not only a statistical one) is indispensable (see, e.g., Kaufmann and Pape 1996).

### 3.2 Results of the factor and the cluster analysis

The results of the *preliminary step* for identifying innovation modes, that is, the *factor analysis* of the fifteen innovation indicators listed in Table 1 are satisfactory (see Table 2). The five factors we extract account for 60% of the total variance. The first factor, capturing 23% of the total variance, reflects the technological and economic significance of process innovations and innovation-related cost reductions. The second factor, accounting for 13% of the variance, represents the innovation input (expenditures for research and for development, respectively) and the science-oriented innovation output (patent applications). The third factor (10% of total variance) refers to the technical and economic significance of product innovations and to the sales of new or significantly improved products. The fourth factor focuses on the total of innovation-related follow-up investments as well as on specific components of these expenses (e.g., outlays for machinery and equipment, or for the introduction of new products on the market). At the core of the fifth factor are the expenditures for some (primarily) IT-related components (hardware, software, training, consultancy, etc.). We conclude that the factor analysis convincingly synthesises the information contained in the fifteen innovation indicators into *five factors*, each representing a specific *orientation* of the innovative activity: “process-orientation” (F1), “science-orientation” (F2), “product-orientation” (F3), “investment-orientation” (F4), and “IT-orientation” (F5).<sup>4</sup>

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<sup>4</sup> Alternative factor solutions based on four or six factors are inferior for the total sample as well as for subsamples covering only one or two cross-sections. In addition, the factor pattern we ultimately use (five factors) is very similar for the total sample and the various subsamples.

Table 2 (*about here*)

Next, we perform a *non-hierarchical cluster analysis* based on the firms' scores for the factors F1 to F5. As the method requires to fixing the number of clusters *in advance*, we calculate alternative solutions in the range of four to seven clusters. In order to determine the *optimal number of clusters*, we take into account three criteria: (a) the statistical properties in terms of the relationship between *within-cluster* and *between-cluster* variance, indicated by the usual criteria such as the expected overall  $R^2$ ; (b) the number of firms per cluster, which, to guarantee a reliable mapping of firms and clusters, should exceed a certain minimum level; (c) a *preliminary* overall assessment of the plausibility of the clusters (“may we effectively interpret the various clusters as different modes (strategies) of innovation?”). It turns out that no solution is clearly superior according to the statistical criterion (a). However, we have to drop the versions with six or seven clusters based on criterion (b). In both cases, the number of firms are too low for at least one cluster, meaning that “more demanding” types of analyses such as those we perform in the Sections 4 to 6 are not feasible. Furthermore, we also disregard the solution with four clusters as it insufficiently differentiates between the clusters, thus violating criterion (c).

We thus arrive at a solution with *five clusters* (see Table 3). It is satisfactory in statistical terms (the expected overall  $R^2$  of 0.44 suggests an acceptable fit of the data to the underlying cluster model), and each cluster contains a large number of firms. Even more important, we can interpret the five clusters as separate innovation modes. The clusters 1 and 2 focus unambiguously on *one* specific factor, i.e. on F2 (science-orientation) and, respectively, F4 (investment-orientation). Cluster 1 thus represents a “science-based strategy”, while cluster 2 stands for an “investment-based strategy”. Cluster 3 shows a strong orientation towards factor F5 (IT-orientation); at the same time, we find for this cluster a large *negative* value for F3 (product orientation), indicating, *in relative terms*, a strong process-orientation. These two findings for cluster 3 point to an “IT/process-oriented strategy”. The remaining two clusters represent strategies that combine two factors. Cluster 4 focuses on F1 (process-orientation) and F3 (product-orientation), indicating a “process/product-oriented strategy”, and, finally, cluster 5 concentrates on F5 (IT-orientation) and F3 (product-orientation), pointing to an “IT/product-oriented strategy”. Cluster 3 and cluster 5 thus represent two different IT-oriented strategies, where the one is process-oriented and the other one product-oriented.

In sum, the cluster analysis yields five categories of firms, which we may interpret, on a *preliminary* basis (see above), as specific modes of innovation. We assess the adequacy of the five innovation modes in more detail in the next subsection, drawing on variables not used in the clustering process (“external criteria”). These serve to evaluate from an *independent and theory-based point of view* whether we *effectively* may interpret the five clusters as specific modes of innovation.

Table 3 (*about here*)

### 3.3 Basic characteristics of the innovation modes

As set out in subsection 3.1 (methodology), we characterise in a second step of the analysis the five innovation modes (clusters), firstly, in terms of the *innovation variables used in the clustering*

*process*, complemented by information on the objectives of innovation that indicate the direction of innovative activities. Secondly, we draw on a set of theory-based innovation-related variables *not* considered in the clustering step, which capture the most important *demand and supply side determinants* of innovation as well as some variables representing the firms' embeddedness in knowledge networks. Finally, we characterise the clusters in terms of some structural attributes of the firms.

Among the *determinants* of innovation (see, e.g., Cohen 2010), we take into account, on the *demand side*, the medium-term market prospects of a firm, the intensity of price competition and of non-price competition in the product markets, and the number of its principal competitors in the world market. On the *supply side*, we include, at firm level, a proxy for the innovation opportunities (measured by a firm's assessment of the potential to generate novelties in and around the field of its activities), a measure of the appropriability of knowledge as well as two indicators of the availability of human capital. We take account of human capital, firstly, as firms well-endowed with highly skilled personnel are in a favourable position to innovate and to absorb knowledge from external sources (Cohen and Levinthal 1989), and, secondly, as human capital is particularly relevant as a determinant of innovative activities of services firms. To characterise a firm's *embeddedness in knowledge networks*, we insert, firstly, variables representing the intensity of use of external knowledge sources in an informal way (customers, several types of suppliers, competitors, consultancy firms, patent disclosures, universities, other scientific institutions, generally accessible sources such as trade journals, conferences, fairs, IT-networks, etc.). Moreover, we take into account a firm's formal (institutionalised) access to external knowledge by way of national and international R&D contracts as well as (long-lasting) R&D co-operations. We include these variables to capture the increasing contribution of external knowledge to a firm's innovation performance, as it is emphasised in the growing literature on "open innovation" (for this concept, see Chesbrough 2003). Finally, we provide information on some structural characteristics of the firms (size, age, export orientation) to get some insight into the composition of the five clusters. For the definition and measurement of the variables used to evaluate the adequacy of the modes of innovation, see Table 4.

Table 4 (*about here*)

In the appendix, we show in detail the mean values of these variables for the five clusters and the total sample (entire business sector). More specifically, we characterise in Table A.2a the clusters in terms of the fifteen *innovation indicators used in the clustering process*. Then we present data for several categories of *variables not used in the cluster analysis*, that is: the objectives of innovation activities (Table A.2b); the supply and demand side determinants of a firm's innovation performance (Table A.2c); some measures representing the formal and informal knowledge network of the firms (Table A.2d); finally, a few structural firm characteristics (Table A.2e).

In what follows, we shortly *characterise the clusters* in terms of these categories of variables. This allows to assessing whether they *effectively* represent specific modes of innovations (innovation strategies). For more details on the pattern of the underlying variables by cluster, we refer the reader to the appendix (Tables A.2a to A.2e).

*Mode 1: High-profile science-based product innovators with a strong internal knowledge base and a dense and highly diversified national and international knowledge network (“science-based strategy”).*

The firms of this cluster pursue a high-profile innovation strategy focused on the generation and the marketing of new products. Innovative activity rests on intensive internal efforts (very large expenditures for R&D, excellently qualified staff) and the embeddedness in a broadly based, internationally-oriented knowledge network; at the core of the latter are science-related and user-oriented informal knowledge sources as well as formal R&D-based relationships (R&D co-operations, R&D contracts). Favourable market conditions (demand perspectives, few competitors) and excellent conditions on the supply side (technological/innovation opportunities, appropriability of knowledge) drive innovative activities. This cluster contains a very high proportion of strongly export-oriented large or medium-sized firms, which, compared to the mean of the entire sample, are concentrated on four high-tech manufacturing industries (53%): chemicals/pharmaceuticals, non-electrical machinery, electrical machinery and electronics/scientific instruments. The cluster contains 1021 companies (18.1% of all firms), with a share in total employment of 22.1%.

*Mode 2: Low-profile investment-based innovators with a weak internal and external knowledge base and a focus on adopting cost-reducing technology (“investment-based strategy”).*

The firms of this cluster pursue a low-profile innovation strategy. They focus on investments, particularly in machinery and equipment, which, in the first place, aim at the adoption of new process technology often generated by other firms, with the objective of reducing production costs. This strategy is characterised by low innovation opportunities, quite poor market conditions (average demand prospects, high price competition), and a weak internal and external knowledge base (human capital, formal and informal knowledge network). This cluster contains quite a high proportion of medium-sized, relatively old companies with an average export-orientation. Compared to the overall mean, the construction sector (8%) and some low-tech manufacturing industries (39%), particularly food/beverages/tobacco, wood products, non-metallic minerals, metal production and metalworking, are the main areas of activity of the firms of this cluster. It contains 1397 companies (24.8% of all firms), with a share in total employment of 26.7%.

*Mode 3: Medium-profile process innovators focusing on the re-organisation of business processes based on high IT-investments and drawing on IT-related external knowledge (“IT/process-oriented strategy”).*

Innovative activities of the firms of this cluster primarily aim at re-organising their business processes. To this end, they heavily invest in IT-hardware and software, training activities and the acquisition of external knowledge. The firms complement their strong internal knowledge base (very large IT-expenditures, highly qualified staff) by drawing, to a substantial extent, on external knowledge informally provided by suppliers of machinery and IT. Other supply side conditions are weak (appropriability) or not more than average (technological/innovation opportunities). This cluster contains a very high share of firms active solely in domestic markets and a substantial share of large companies; firm age is about equal to the overall mean. The firms of this cluster are strongly

concentrated on the services sector, primarily on two knowledge-intensive service industries (31%), i.e., banking/insurance and business services (other than IT-/R&D services), and, to a lesser extent, on another three service industries that have a high potential for process-oriented IT (23%), i.e., wholesale trade, transport/storage/logistics and publishing/printing. This cluster includes 802 companies (14.2% of all firms), with a share in total employment of 18.9%.

*Mode 4: Low-profile process-product innovators with a weak internal knowledge base not compensated for by external knowledge (“process/product-oriented strategy”).*

The firms of this cluster pursue a low-profile innovation strategy focusing on (incremental) process and/or product innovations. Striking are the weak supply side conditions (low technological opportunities, weak external knowledge network). With respect to the other variables, this category of firms does not much differ from the entire business sector. The cluster contains a particularly high share of small firms, whereas the other structural firm characteristics (firm age, export orientation, industry affiliation) are similar to those of the total sample. This cluster consists of 1555 companies (27.5% of all firms), with a share in total employment of 23.1%.

*Mode 5: High-profile IT-based product innovators with a strong IT-related internal knowledge base and a highly diversified informal knowledge network along the value chain (“IT/product-oriented strategy”).*

The firms of this cluster pursue a high-profile IT-related innovation strategy focusing on the development of new products and markets. The basis of the innovative activity are large internal IT-expenditures and innovation-related investments in training and the introduction of new products on the market. The firms are active in niche markets (dominance of non-price competition) and benefit from high technological/innovation opportunities. They strengthen their internal knowledge base by exploiting a wide array of (primarily informal) external knowledge sources, with firms along the value chain and generally accessible sources (fairs, professional journals, computer networks) at the core. Companies of this cluster, to a high extent, serve only domestic markets. Moreover, a particularly large share of firms are small and young. Compared to the entire sample, the firms are present strongly in knowledge-intensive industries (23%), i.e. electronics/instruments, banking/insurance and IT-/R&D-services, as well as in wholesale and retail trade (20%). The cluster consists of 870 companies (15.4% of all firms), with a share in total employment of only 9.1%.

Altogether, it turns out that each cluster shows a very specific configuration of the variables used in the cluster analysis (for the detailed results, see Table A.2a in the appendix). More important, however, is the fact that we find for each cluster a specific pattern with respect to the demand side and supply side variables which, according to the economics of innovation, determine a firm's innovation performance (for the detailed results, see the Tables A.2c and A.2d in the appendix). As already mentioned, we use, on the demand side, measures representing the firms' market prospects, type and intensity of competition, and market concentration. On the supply side, we include indicators of the technological/innovation opportunities, the appropriability of knowledge, the availability of human resources, and a firm's embeddedness in formal and informal knowledge

networks. In all respects, the differences between the five clusters are accentuated and clearly interpretable from an economic point of view.

Against this background, we may safely conclude that the *five clusters* are *specific modes of innovation* (innovation strategies). Two of these modes represent high-profile product innovators, with one of them science-based (cluster 1), and the other one IT/product-oriented (cluster 5). Another two modes capture low-profile innovators, the one including investment-based innovators/adopters of cost-reducing process technology (cluster 2), and the other one referring to (incremental) process and/or product innovators (cluster 4). Finally, we identify an innovation mode representing medium-profile innovators, which concentrate on re-organising their business processes based on an intensive use of IT (cluster 3).

### **3.4 Comparison with other firm-level studies**

A comparison with the classification of innovation strategies suggested in previous firm-level research is difficult. In general, studies including *many indicators* end up with a relatively large number of innovation modes. For example, Tiri et al. (2006), using 35 indicators, identify seven innovation clusters, whereas others find only four different strategies, as they include rather few innovation variables (e.g., de Jong and Marsili 2006). Moreover, the identification of innovation modes and their characteristics also depend on the *type of indicators* taken into account. A review of the available studies shows that the majority of researchers uses a specific mix out of seven categories of innovation-related variables: (a) innovation inputs, (b) innovation outputs, (c) market-related innovation indicators, (d) non-technological innovations, (e) innovation objectives, (f) appropriability of knowledge, and (g) formal and informal external knowledge sources. Some researchers draw on five or six of these subsets of indicators (Tiri et al. 2006; Frenz and Lambert 2012; Srholec and Verspagen 2012; Wziatek-Kubiak et al. 2013; Sanchez 2014), whereas other authors use only three or four of them (Cesaratto and Mangano, 1993; Hollenstein 2003; de Jong and Marsili 2006; Leiponen and Drejer 2007). Moreover, the different firm-level studies, even if they include the same *categories* of variables, do not use the same sub-indicators and/or attach different weights to specific aspects of a certain group of measures.

In the present paper, the identification of innovation modes is only the first step necessary for tackling the three core questions of our research, i.e. the dynamics of innovation strategies, the intra-industry heterogeneity of innovation modes, and, finally, the relationship between the choice of a specific innovation strategy and firm performance. Therefore, we abstain from a one-to-one comparison with the various classifications suggested in previous research. Nevertheless, we may indicate that several studies, at least in essence, also (tend to) identify two (or perhaps three) of our five innovation clusters: “high-profile science-based innovators” (cluster 1), “low-profile investment-based innovators/adopters” (cluster 2), and, as a tendency, “low-profile process/product-oriented innovators” (cluster 4). In contrast, the clusters 3 and 5, for which an intensive use of IT is constituent, is not a core element of the innovation strategies identified by other researchers. This difference, in the first place, reflects the fact that many studies do not include any *IT-related*

*indicators*, which is the case, for example, if the data stem from the “Community Innovation Survey (CIS).<sup>5</sup>

Finally, we remind that, with the exception of Hollenstein (2003), none of the researchers evaluates the adequacy of their innovation clusters from an independent (external) point of view, i.e., using for this purpose some variables that, according to the theory, determine a firm’s innovation activity.

## 4 Switches between innovation modes over time

### 4.1 Aim and procedure

The innovation mode a firm chooses at a certain point in time may not be optimal anymore if the innovation-related environment changes. For example, the market entrance of new competitors or a structural deterioration of market prospects may enforce a firm to adapt its innovation strategy. Besides, a technology push may open up new market opportunities a company only can seize by changing its strategy. Furthermore, if a firm is able to enhance its innovation-related capabilities in the course of time, e.g., with respect to IT, it may become optimal to switch to an IT-based strategy in order to enter new markets or to reduce production costs.

To the best of our knowledge, this study is the first *large-scale* analysis dealing *at the firm level* with the *dynamics* of innovation modes.<sup>6</sup> We are able to gain some insight into the change of innovation strategies over time, although the dataset is an *unbalanced* panel. Because of this incompleteness, we take into consideration only firms for which information is available for *two successive waves* of the three-yearly survey. In so doing, we get a sample of 1656 observations, which indicates whether a firm changes its innovation strategy in the course of a *three-year period* (from 1999 to 2002, 2002 to 2005, or from 2005 to 2008). The analysis thus focuses on adjustments in the *short* run. Because a switch from one to another innovation strategy is likely to happen more often in the medium or long run, the present analysis tends to underestimate the frequency of strategic changes.<sup>7</sup>

We assume that a firm decides on modifying its innovation strategy in *two steps*. Firstly, the company determines whether it should stick to the current strategy or whether it is more appropriate to move to another one (whatever the latter may be). In this case, without specific information with respect to changes of the firm’s innovation-related environment, the probability of switching to *any*

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<sup>5</sup> There is a *certain* similarity between cluster 3 (“IT-based process-oriented strategy”) and one of the innovation modes identified, based on CIS data, by Frenz and Lambert (2012) or Srholec and Verspagen (2012), which captures “process-related organisational innovations”, however without mentioning the use of IT.

<sup>6</sup> There are a few studies dealing with the *change* of innovation strategies, which, however, primarily serve as theoretical explorations. For example, Utterback and Abernathy (1975) provide a theoretical framework for analysing the long run dynamics of firm strategies over the product life cycle, complemented by an empirical assessment of the feasibility of the model based on data for 120 firms. Malerba and Orsenigo (1993), in turn, suggest that firms adapt their innovation strategy as a response to a change of the characteristics of the prevailing technological regime, and illustrate this proposition for three selected industries.

<sup>7</sup> The analysis assumes that the results of the cluster analysis presented in the previous section, which uses the total sample (four waves of the survey), do not much change if we perform the same analysis with data stemming from only two successive waves of the survey. It turns out that this assumption is quite realistic, as the characteristics of the five clusters that we find for the total and the reduced samples are very similar.

another innovation strategy is 50%, or, more realistically, somewhat less because of switching costs. Secondly, given a company decides to switch to another strategy, it may choose to move to one of four alternative modes of innovation, i.e., the five innovation strategies identified in Section 3 minus the one the firm currently pursues. Therefore, the probability of switching *to one specific* of the four strategies is 25%, assuming that the switching costs are largely the same for the transition to each of the four alternatives.

## 4.2 Frequency of a change of strategy

We find that 1049 of the 1656 firms (63%) switch to another mode of innovation in the course of a three-year period. This percentage is significantly higher than the (a priori) expected probability of (less than) 50%. Furthermore, it turns out that the frequency of a strategic change differs among the five clusters. It varies in the case of the strategies 2 to 5 in the range of 61% (firms initially belonging to cluster 2) and 69% (companies affiliated at the outset to cluster 4 or 5). In contrast, companies of cluster 1 do not change their innovation strategy more often than expected a priori (51%). Altogether, we conclude that, even *in the short run*, the share of firms switching from the current to another innovation strategy is high, what is true in total as well as in the case of four out of the five innovation modes. This finding may indicate that the innovation-related environment changes quite rapidly and that a large number of companies is able to shift its innovation strategy within a short period.

To complement these findings, we calculate the frequency of a change of strategy for the 383 observations belonging to *non-adjacent* cross-sections. In this case, the time elapsed between two waves of the survey amounts to six years (1999 to 2005 and 2002 to 2008, respectively) or even to nine years (1999 to 2008). We find that 69% of these companies adapt their strategy in the course of such a longer period as against 63% over three years. Hence, as expected, a change of innovation strategy takes place more often in the medium or longer run. However, quite surprisingly, the difference between the two percentages is rather small.

In the following subsection, we focus on the shifts of the firms' innovation strategies that occur in the course of three years. We thus exclusively analyse the pattern of changes of the 1656 companies belonging to *adjacent cross-sections* (i.e. *successive* waves of the survey).

## 4.3 Direction of a change of strategy

Table 5 shows *vertically (columns)* the *number* of firms a specific cluster (innovation strategy) attracts from each of the other clusters, and, additionally, the total number of these changes ("*inflows*"). For example, cluster 1 attracts 67 firms pursuing initially strategy 2; in total, cluster 1 gains 191 companies from the other four clusters. In the same way, the table indicates *horizontally (rows)* the *number* of firms moving from a specific cluster to each of the other four clusters as well as the sum of these changes ("*outflows*"). For example, 55 companies switch from cluster 1 to cluster 2; in total, 171 firms leave cluster 1 to pursue one of the other four strategies.

In a first step, we do not take into account the substantial number of firms which do not change their strategy (i.e., we exclude 607 of the 1656 observations). Accordingly, the *diagonal* in Table 5 and in the Tables 6a and 6b remains empty. We choose this procedure because in our *two-step approach*, as

already mentioned, the (a priori) expected probability of shifting from the initial strategy to *any* of the alternative modes of innovation differs from that of switching to *one specific* of the other four clusters (50% vs. 25%). The interpretation of the results would be more complicated, if we would include the firms sticking to their current strategy. However, we shall take account of this information later on.

Table 5 (*about here*)

In the following, we do not comment on Table 5, which shows the *absolute number of transitions* from one to another cluster. This table only serves to calculate the ratio of the number of firms *attracted* by a specific cluster *from other ones* (*inflow*) to the number of firms *moving away* from that cluster *to other ones* (*outflow*). We show these *ratios of inflows to outflows* in Table 6a.

To provide an example of how to read Table 6a, we firstly comment on cluster 1 (science-based strategy). The ratio of 1.22 shown in row 2 of column 1 means that cluster 1 (science-based strategy) attracts 22% more firms from cluster 2 (investment-based strategy) than it loses to that cluster. Cluster 1 benefits even more from the net inflows from cluster 4 (process/product-oriented strategy); the corresponding ratio amounts to 1.38. In contrast, we observe that clearly more firms switch from cluster 1 (science-based strategy) to cluster 5 (IT/product-oriented strategy) than it is the case in the opposite direction. According to the ratio shown in the cell at the bottom of the first column, *cluster 1 (science-based strategy)* is a clear *winner* of the shifts from and to the other strategies; the total inflows of firms are 12% higher than the total outflows.

The opposite is true for *cluster 4 (process/product-oriented strategy)*, which, in total (cell at the bottom of column 4), loses 17% more firms than it attracts from all other clusters (overall ratio of 0.83). In this case, the large net outflows to the clusters 1 and 2 (science-based strategy and investment-based strategy, respectively) stand out. For *cluster 2 (investment-based strategy)*, we record in total a largely balanced ratio of inflows to outflows (ratio of 1.03). In this case, the ratios for the individual strategic shifts strongly diverge, depending on the specific strategy considered. The large net losses due to the moves from and to cluster 3 (IT/process-oriented strategy) and from and to cluster 1 (science-based strategy) practically even out the very high net inflows of firms initially belonging to cluster 4 (process/product-oriented strategy). *Cluster 3 (IT/process-oriented strategy)*, to quite a significant extent, also is an overall winner as shown in the cell at the bottom of column 3. The net gain of 9% primarily reflects the large positive balance of the inflows from and outflows to cluster 2 (investment-based strategy). Finally, the Table 6a shows that *cluster 5 (IT/product-oriented strategy)* is on the winning side as well, although the total net inflow rather small (ratio of 1.06). In this case, the net gain reflects, in the first place, high net inflows from cluster 1 (science-based strategy).

To *show at a glance the direction and relevance of switches* from one to another innovation strategy, we “transform” the *quantitative* values of the ratio of inflows to outflows (Table 6a) into a *qualitative* picture of the net gains or losses of firms due to the transitions from and to the five strategies (Table 6b). In addition, we provide for each mode of innovation the overall balance of the changes of strategy. We only depict *substantial deviations from a balanced relationship* between

inflows and outflows. A positive (negative) *sign* in a cell of a specific column represents a net gain (loss) from the moves between two specific clusters. The sign in the cell at the bottom of a column indicates the overall net gain (loss) due to the shifts between the strategy considered and all alternative strategies. The *number of positive (negative) signs* shown in a specific cell roughly indicates, based on Table 6a, the *size* of the net gains (losses) from the corresponding switch of strategy or from the total of such shifts. For the *definition of the “number of signs* (i.e. one, two or three) that reflect different ranges of the deviations from the value 1 (where inflows and outflows are equal), see the notes <sup>b</sup> and <sup>c</sup> of Table 6b; if the net gain (loss) is small or negligible, the corresponding cell remains empty. The *three slashes* on the diagonal reflect the fact that, at this stage, we do not consider the share of firms sticking to their current strategy.

Table 6a (*about here*)

Table 6b (*about here*)

The last row of Table 6b shows that cluster 1 (science-based strategy) and, though less pronounced, the clusters 3 and 5 (IT/process-oriented strategy and IT/product-oriented strategy) are the overall winners of the switches between the five innovation strategies. In contrast, cluster 4 (process/product-oriented strategy) is the prime loser of the shifts of strategies. In the case of cluster 2 (investment-based strategy), the total of inflows from the other clusters is quite similar to the total of outflows. We do not comment on the ratios of inflows from each individual cluster to the corresponding outflows shown in the rows 1 to 5 of Table 6b, as we already discussed them above.

At this point, we have to take into account that the “attractiveness” of a cluster does not only depend on the frequency of shifts between the five modes of innovation but also on the extent the firms of the individual clusters *stick to the initial strategy* (607 out of a total of 1656 observations). We remind that the share of firms not switching to a new strategy is quite similar in the case of four of the five innovation clusters, i.e., the clusters 2 to 5 (see the previous subsection). Hence, the decision to change (or not to change) the current innovation strategy does not substantially influence the *relative attractiveness* of these four clusters. The same is not true for the science-based strategy (cluster 1). In this case, the proportion of firms sticking to the original mode of innovation (49%) is substantially higher than the corresponding share in the rest of the sample (35%). The science-based strategy is thus the most attractive mode of innovation for two reasons: (a) it attracts more firms initially pursuing another innovation strategy than it loses companies as a consequence of moves to another innovation mode (net winner), and (b) the share of firms sticking to the initial strategy is particularly large.

### 4.3 Assessment of the results

The overall frequency of the switches from one to another strategy of innovation is high, given that we only can analyse changes occurring within a period of three years. The pattern of the shifts between the five innovation strategies is highly plausible, as it is in line with the structural change required in a high-income economy such as the Swiss one. In an economically advanced country, there is a permanent pressure to increasing the innovation intensity of firm activity. In accordance

with this need, the science-based strategy (cluster 1) becomes more attractive over time. The same is true, though to a somewhat lesser extent, for the two IT-related strategies (cluster 3 and 5). The firms seem thus to be able to integrate within a short period a “disruptive” type of technology like IT in their innovation strategy. On the other hand, the process/product-oriented strategy (cluster 4) is the main loser of the observed shifts between the five innovation modes. This finding is not surprising, as many firms of this category primarily aim at generating incremental innovations. In the medium and longer term, an upgrading of the innovation activities of this quite large segment of the Swiss economy, which covers about a quarter of the sample, is indispensable. The concordance of the dynamics of innovation strategies and the direction of the structural change required in the highly advanced economy of Switzerland are additional evidence for the adequacy of the five modes of innovation identified in Section 3.

## **5 Intra-industry heterogeneity of innovation modes**

### **5.1 Theoretical background**

The *technological regime approach* argues that the firms belonging to a specific industry pursue similar innovation strategies, as their innovation-related environment is largely the same. The latter reflects structural characteristics such as technological opportunities, appropriability conditions, cumulativeness of knowledge, sources of knowledge, etc. (see, e.g., Nelson and Winter 1977; Dosi 1982). Consequently, this approach postulates that the patterns of innovation are *homogenous at the industry level*, meaning that the intra-industry variance of innovation strategies is small (“homogeneity hypothesis”). In this tradition, several empirical studies identify specific innovation patterns at the aggregate level (2-digit or groups of 2-digit industries) for manufacturing (e.g., Pavitt 1984), services (e.g., Evangelista 2000) and the business sector as a whole (e.g., Castellacci 2008; Peneder 2010).

In contrast, the *strategic management literature* emphasises the specifics of the innovation strategies of each company. The individual firm seeks to create a competitive advantage by drawing on some unique technological, organisational, human and other resources and capabilities. Hence, innovation patterns are specific to firms rather than industries, which implies a substantial *intra-industry heterogeneity* of innovation strategies (“heterogeneity hypothesis”). This approach builds on several (effectively quite similar) concepts of the firm such as the “resource-based” (Wernerfelt 1984) or “dynamic capability” view of the firm (Teece et al. 1997), or the concept of the “knowledge-based company” (Kogut and Zander 1993). Besides, Srholec and Verspagen (2012) argue that the evolutionary process of selection, for various reasons, does not completely wipe out the pre-existing variance of the firms’ innovation strategies; hence, there always remains a certain amount of intra-industry heterogeneity (see also Knott 2003).

### **5.2 Empirical evidence based on firm-level data**

*Firm-level studies* published in the course of the last twenty years provide, inter alia, information on the distribution of firms pursuing different innovation strategies *within 2-digit industries* (see, e.g., Cesaratto and Mangano 1993; Hollenstein 2003; de Jong and Marsili 2006; Tiri et al. 2006; Srholec

and Verspagen 2012). Contrary to the technological regime approach, these analyses throughout find a substantial intra-industry variation of innovation modes, which seems to be consistent with the strategic management view (heterogeneity hypothesis). Nevertheless, most of this empirical work shows that one or two strategies are significantly more common than other ones in quite a few industries, a finding that, to some extent, qualifies the evidence for the heterogeneity hypothesis. In addition, it is generally questionable whether the observed heterogeneity within 2-digit industries allows to rejecting the homogeneity hypothesis, as branches at this level of aggregation mostly cover very different lines of production (Archibugi 2001). Therefore, it is indispensable to analyse the intra-industry variance of innovation strategies at a higher level of disaggregation.

To the best of our knowledge, Leiponen and Drejer (2007) is the only investigation based on *highly disaggregated industry data*, representing, with few exceptions, the 4-digit NACE classification.<sup>8</sup> The results of this detailed analysis referring to the Finnish economy<sup>9</sup> are in line with the heterogeneity hypothesis, as they point to a high intra-industry variation of innovation strategies. This finding is not self-evident, as highly disaggregated industries should be more homogeneous in terms of their productive activities than more aggregated branches. However, as the study of Leiponen and Drejer (2007) rests on a very thin database in terms of the number of industries considered, it would be premature to reject the homogeneity hypothesis. Consequently, we investigate the relative merits of the two opposite hypotheses making use of the large dataset for Switzerland, which allows an analysis based on 153 industries (4-digit NACE classification), as against only 21 in the study for Finland.<sup>10</sup> In so doing, we may expect a more reliable assessment of the heterogeneity hypothesis.

In advance of presenting the results of the disaggregated analysis for the Swiss economy, it is sensible to have a look at the firms' distribution over the five clusters identified in Section 3 *at a higher level of aggregation*. More specifically, we show in Table 7 the distribution (a) for 29 industries that largely represent the 2-digit classification, and (b) for five sectors, i.e. high-tech manufacturing, low-tech manufacturing, construction, knowledge-intensive services and, finally, "other services" (that are less knowledge-intensive). The table reveals that the five innovation modes are present in all (but one) 2-digit industries. However, in seven industries, more than 40% of the companies belong to one specific cluster, and in another thirteen industries, the share of the largest cluster is in the range of 35% to 40%. In sum, we observe for quite many 2-digit industries a certain concentration of the firms on one innovation mode (in some instances, on two clusters), whereas for other branches, we find a rather wide distribution over the five clusters.

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<sup>8</sup> The study, "*nominally*", uses a 5-digit classification. However, as the fifth digit is zero in the case of 86% of the 35 industries considered, the analysis *effectively* refers to the 4-digit classification.

<sup>9</sup> This investigation, in parts, combines data for Finland and Denmark. However, an analysis of the intra-industry distribution of firms by cluster is possible only for Finland as the Danish dataset is much too small.

<sup>10</sup> As argued below, the Finnish data used by Leiponen and Drejer (2007) do not allow a reliable analysis for all industries listed in the appendix A of their study. We only consider 21 out of 35 industries. We drop 14 industries that include only 6 or 7 companies, as we suspect that in these industries the distribution of the firms over the clusters is more or less random.

Despite these mixed results, there is a statistically significant *association between cluster and industry affiliation*. In the construction sector and some low-tech industries, many firms pursue an investment-based innovation strategy (cluster 2). The firms of other low-tech industries are primarily present in cluster 4 (process/product-oriented strategy). The majority of high-tech companies prefers a science-based strategy (cluster 1), but in two industries of this subsector, cluster 2 (investment-based strategy) is the most important innovation mode. In some of the knowledge-intensive service industries, the firms pursue to a significant extent an IT/process-oriented strategy (cluster 3). In the subsector “other services”, which includes less knowledge-intensive services companies, no innovation strategy generally stands out. Nevertheless, three of these industries have a focus on one (but not the same) cluster. Finally, the IT/product-oriented strategy (cluster 5) is the most important mode of innovation only for two of the 29 industries, which both belong to the services sector.

Table 7 (*about here*)

Altogether, the examination at the *2-digit level* does not allow to decide whether the firms’ innovation strategies are homogeneous within industries (technological regime approach), or, whether they substantially differ within the same branch (strategic management view). To get a more meaningful picture, we analyse the distribution of firms over the five clusters for *4-digit NACE industries*, whose productive activities should be more homogeneous than they are in 2-digit branches. To this end, we more or less replicate for Switzerland the study of Leiponen and Drejer (2007). In so doing, we get a reference for the assessment of our results.

The two researchers show for Finland three alternative sets of results for the intra-industry distribution of firms over the five clusters they identified in a previous step of their analysis.<sup>11</sup> These differ with respect to the minimum number of companies an industry must contain to be included in the analysis (six, eight and ten firms, respectively). We suspect that the results based on a cut-off point of only six observations are not reliable, as in this case, the distribution over five clusters tends to be random. Therefore, we only take into account industries with “at least eight” and, alternatively, “at least ten” companies. Our large dataset allows to analysing the intra-industry distribution of firms by cluster for 153 branches based on a cut-off point of eight firms, and for 126 branches if we rely on a threshold of ten companies. In the Finnish case, the corresponding numbers of industries are 21 and 14, respectively. In view of these small numbers of industries in the Finnish study, a large-scale replication of the analysis is compelling in order to get results that are more reliable.

In column 1 of Table 8, we present a *summary of the findings* with respect to the intra-industry distribution of firms over the five innovation clusters for the *Swiss economy*. Table A.3 in the appendix shows the detailed results for each of the 153 industries. In column 2 of Table 8, we provide the same information, as far as available, for *Finland*, drawing on Leiponen and Drejer (2007: Table 6 and Table A1 in the appendix).

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<sup>11</sup> The five clusters used in their analysis partly differ from ours, primarily because the Finnish and the Swiss study diverge in terms of the variables used to identifying and characterising innovation modes. For the problems encountered in comparing innovation clusters between different studies/countries, see subsection 3.4.

The upper part of Table 8 (row 1.A to 2.B) shows the share of industries *not dominated by a specific cluster*. In line with Leiponen and Drejer (2007), we define a cluster as dominant if at least 50% of the firms of an industry belong to *one specific cluster*. Considering the branches with “*eight or more firms*” (row 1.A), we find for Switzerland that 71% of the 4-digit industries do not have a dominant cluster, as against 61% in the case of Finland. Alternatively, if we take into account only the industries with “*ten or more companies*” (row 1.B), the share of branches without a dominating cluster, as one would expect, is higher in both countries (78% and 80%, respectively). These findings point to a high intra-industry heterogeneity of the innovation strategies of firms. The amount of heterogeneity is quite similar in the two countries, perhaps even somewhat larger in the Swiss case. In view of the highly different number of industries included in the analysis for the two countries, it is rather surprising, that the degree of heterogeneity is largely the same.

Table 8 (*about here*)

To check the *robustness of these results*, we consider, alternatively, only 4-digit industries that cover *clearly specified* activities (data only for Switzerland). To this end, we exclude three types of industries (see Table A.3, part B in the appendix). Firstly, branches that are a *residual* collection of firms (e.g., “*manufacture of machinery not elsewhere classified*”); secondly, industries containing “*other activities*” not clearly specified (e.g., “*activities of other transport agencies*”); and, finally, branches representing *general* activities of a larger sector (e.g., “*general mechanical engineering*” as an *unspecified part* of the larger group “*manufacture of fabricated metal products*”). By excluding these three categories, we end up with 128 industries (with “*at least eight firms*”) and 105 industries (with “*at least ten firms*”). It turns out that the reduction of the number of branches (amounting to about 16%) hardly changes the results we get for all industries (see Table 8: row 2.A vs. row 1.A and row 2.B vs. row 1.B). Furthermore, (very) big companies may distort the results, as they mostly are active in several fields of activities. However, calculations where we exclude firms with more than 1000 employees yield more or less the same results, which, however, is not surprising as about 95% of the sample are firms with less than 1000 employees).

In the lower part of Table 8, we show results for *two types of indicators* that provide some additional evidence regarding the intra-industry heterogeneity of innovation modes. The *first type* refers to the *spread of the distribution of firms over the five clusters*. According to row 3.A, 59% of the 4-digit industries (containing at least eight firms, i.e. 153 industries) appear in all five clusters (data only for Switzerland). Moreover, row 3.B indicates that, in the Swiss case, 88% of the industries appear in at least four of the five clusters, as against 63% in the Finnish economy. The *second type of indicator* considers the matter from the *perspective of the individual clusters* (last row of Table 8). For Switzerland, we find that all five clusters contain firms from at least 75% of the 153 industries, as against only 3 out of 5 clusters in the case of Finland.<sup>12</sup> The results based on the two additional types of indicators confirm the findings presented in the upper part of Table 8. Altogether, we

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<sup>12</sup> The choice of the 75% criterion is arbitrary, but we stick to it, because otherwise we cannot not compare the results with those for Finland.

conclude that, independent of the indicator used, the intra-industry heterogeneity of the firms' innovation strategies is high in both countries, and even higher in Switzerland than in Finland.

One may object that the threshold used so far to distinguish between *dominating* and *not dominating* clusters is too high ("50% of the firms of an industry belong to one specific cluster"), given that the (a priori) expected probability of a firm to choosing one out of five innovation strategies is 20%. Therefore, we check the robustness of the results using a *threshold of 40%*, i.e. a cluster is dominant if at least 40% of the firms of an industry belong to *one specific cluster*. In the Swiss case, we find that the share of 4-digit industries, which, according to this criterion, are *not dominated* by one specific cluster substantially decreases if we use a 40%-threshold rather than one of 50%. More specifically, we obtain a reduction from 71% to 46% for industries with at least eight companies, and from 78% to 51% for industries with at least ten firms.<sup>13</sup> The difference, however, is much smaller if we only consider industries with *clearly specified activities* listed in *part A of Table A.3* in the appendix. In this case, the share of industries not dominated by one specific cluster decreases not very much if we reduce the threshold from 50% to 40%. We get a reduction from 69% to 63% for industries with at least eight firms, respectively, from 75% to 68% in the case of industries with at least ten firms. In sum, the robustness checks reported on in this and the previous paragraph reduce the heterogeneity to some extent, but the basic findings still support the heterogeneity hypothesis.

However, we remind that quite many *2-digit industries* exhibit a certain concentration of firms on one or two specific clusters (see above, Table 7). Hence, the results at the 2-digit and the 4-digit level, to a certain extent, seem to contradict each other. However, this is not necessarily the case, as the intra-industry distribution of the firms over the five clusters may be similar for the 4-digit and the 2-digit industries to which they belong. We investigate this proposition based on data for the industries with at least eight companies whose activities are clearly specified (part A of Table A.3 in the appendix). We only consider 4-digit industries where the distribution of the firms over the five clusters shows one or two peaks (which is true for about 85%). We find that the share of industries showing the *same* peak (or the *same two* peaks) at the 4-digit and the corresponding 2-digit level is in the range of 50% to 60%. The distribution of the firms over the five clusters at the two levels of aggregation is thus similar for quite a large share of industries. The concordance is somewhat higher for high-tech and low-tech industries (range of 55% to 65%) than for knowledge-intensive and other service industries (range of 50% to 55%). Altogether, we conclude that the discrepancy of the results for 4-digit and 2-digit industries is not very large, but there remains a certain contradiction of the findings at the two levels of aggregation.

### 5.3 Assessment of the results

To sum up, we find that the innovation strategies of firms quite strongly vary within highly disaggregated industries (4-digit level), which, by definition, are relatively homogenous in terms of their production activities. At the same time, it turns out that the distribution of firms over the five

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<sup>13</sup> Table A1 in the appendix A of Leiponen and Drejer (2007) allows to calculating also for Finland the share of industries without a dominating cluster based on a *threshold of 40%* (instead of 50%). We find that in this case the share of industries without a dominating cluster decreases by the same order of magnitude as in the Swiss economy.

innovation clusters for a substantial proportion of 4-digit industries is similar to that of the corresponding 2-digit industries.

This pattern of results indicates that a firm has a substantial room of manoeuvre for making strategic innovation-related choices within narrowly defined activities (4-digit). However, some structural factors common to many companies of a more aggregated industry (2-digit) may reduce the number and type of feasible strategies. Such restrictions primarily reflect structural characteristics of the firms' innovation-related environment such as technological opportunities, appropriability conditions, cumulativeness of knowledge or external knowledge sources, which, according to the technological regime approach, are similar for firms belonging to the same industry.<sup>14</sup>

Altogether, we conclude that the empirical results presented in this section, *primarily* support the *strategic management view* (heterogeneity hypothesis). However, the evidence may not be strong enough to clearly rejecting the technological regime approach (homogeneity hypothesis). We thus only partly agree with Leiponen and Drejer (2007), which unambiguously favour the heterogeneity hypothesis.

## 6 Innovation modes and firm performance

### 6.1 Hypotheses and model specification

In this final section, we analyse whether a firm is able to gain a competitive advantage by choosing a specific *innovation strategy* (innovation mode). If econometric estimates confirm this view, one may conclude that the *strategic management* of innovative activities is a lever to improve a firm's market position. In contrast, if it turns out that a company's *industry affiliation* is the dominant variable to explain firm performance, *the technological regime approach* would be more appropriate as a framework for analysing the firms' innovation behaviour. If both a firm's innovation strategy and its industry affiliation are positively associated with firm performance, we shall conclude that the two sets of variables are *complementary*. In this case, it is sensible to look at the *relative importance of the two sets of variables* for explaining firm performance. The results of the model estimates should allow a differentiated assessment of the appropriateness of the two basic hypotheses with respect to the firms' innovation strategies. The findings add to the evidence provided in the previous section dealing with the intra-industry heterogeneity of innovation modes.

For the empirical analysis, we use *labour productivity* as a proxy of a firm's competitiveness (dependent variable). The first row of Table 9 shows the average of this variable for the five clusters (innovation modes) as well as for the total sample. The other rows of the table display the mean values of the independent variables we employ for explaining a firm's labour productivity. For

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<sup>14</sup> This conclusion echoes the findings of the study of Peneder (2010) which rests on the "technological regime approach". He identifies, on the one hand side, some structural characteristics (as those mentioned in the text) of innovation patterns at the 2-digit industry level, but, on the other hand, shows that the strategies pursued by firms affiliated to the same industry vary quite a lot.

model estimation, we use pooled data stemming from the four waves of the Swiss Innovation Survey conducted in the period 1999 to 2008.<sup>15</sup>

The average labour productivity, as indicated in Table 9, substantially differs among the five clusters. It varies between 157 thousand CHF in cluster 2 and 187 thousand CHF in cluster 3. However, simply comparing these averages between the five clusters does not allow to assessing whether there is a significant association between the choice of a specific innovation mode and labour productivity, since other factors than cluster affiliation are likely to influence firm performance as well, or do so even to a higher extent.<sup>16</sup> For example, it is not surprising that firms which intensively use physical capital (high capital to labour ratio; see row 2 of Table 9) achieve, on average, a higher labour productivity than companies whose production is less capital intensive (see cluster 3 vs. cluster 2 and 4, respectively).

Table 9 (*about here*)

Against this background, we specify a model explaining a firm's labour productivity based on *four categories of variables*. The *first* one represents the firms' innovation strategies. To specify these variables, we apply the procedure used by Frenz and Lambert (2012) and Sanchez (2014). Accordingly, we capture the five innovation strategies by inserting for each of them the firms' factor scores we used as input for the cluster analysis that served to identifying the modes of innovation (see Section 3). Based on the strategic management view, we expect that the coefficients of the five innovation strategies are positive, meaning that the choice of a specific innovation strategy that reflects the particular capabilities of a firm yields a productivity premium. The *second* group of variables represents the classical input factors of a production function (intensity of use of physical, human and R&D capital). The coefficients of these variables should be positive. *Thirdly*, we control for two structural firm characteristics (firm size, foreign ownership), with both variables expected to exert a positive influence on productivity. Large firms benefit from economies of scale and scope as well as from market power, while foreign firms have to be more productive than domestic ones to compensate for higher transaction costs. *Fourthly*, we insert 28 industry dummies (2-digit level) in order to capture the productivity effects that are common to all firms of a specific industry. The technological regime approach would imply that the coefficients of the industry dummies are jointly significant. However, we also have to take into account that these dummies capture the influence on productivity exerted by variables not explicitly specified in the model, thus serving to prevent an "omitted variable bias".

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<sup>15</sup> The sample employed for model estimation contains 4964 observations as against 5645 used in the cluster analysis presented in Section 3. The difference is due to the fact, that we exclude (a) companies with less than 10 employees, as these notoriously provide unreliable information on labour productivity and capital intensity, and (b) firms with extreme values for core variables. The reduction of the number of observations, which amounts to 12%, hardly changes the distribution of firms by cluster.

<sup>16</sup> Some studies present such averages but, surprisingly, do not use the underlying firm-level information to estimate a productivity equation. A recent example is Tiri et al. (2006), which provide cluster-specific average values of labour productivity and some variables that would be appropriate to identify, at firm level, an association between cluster affiliation and firm performance.

Hollenstein (2003) applies largely the same approach for analysing the impact of specific innovation strategies on labour productivity of *services firms*. His model contains three out of the four categories of explanatory variables we take into account in the present paper; the only exceptions are the two structural firm characteristics, i.e. firm size and foreign ownership. However, the omission of these two variables does not affect the overall pattern of explanation (see below). To the best of our knowledge, there are only three further studies, which analyse the relationship between innovation strategies and firm performance (Frenz and Lambert 2009, 2012; Sanchez 2014). These papers take into account three sets of variables: (a) the firms' innovation strategies, (b) a few structural firm characteristics (in this respect, there are some differences), and (c) industry dummies (2-digit) or, in the case of Sanchez (2014), only a sector dummy (manufacturing yes/no). These studies neglect the influence of the production inputs, which, from a theoretical point of view, is a serious deficiency. A production function framework is indispensable for analysing the productivity effect of a firm's innovation activity. Against this background, it is not surprising that the empirical results of the three papers significantly differ from the findings of Hollenstein (2003) and from those of the present analysis (see below, subsection 6.3).<sup>17</sup>

Finally, it is necessary to point to an econometric problem, arising from the fact that we perform model estimates based on (pooled) cross-section data. In this case, although we use three time dummies capturing specific characteristics of the individual waves of our survey (different rates of response, varying macroeconomic conditions, etc.), the variables could be endogenous, meaning that the estimated parameters may be biased. Therefore, rather than making causal claims, we interpret the estimated coefficients as *conditional correlations*. Nevertheless, this restriction does not preclude an evaluation of our hypotheses, particularly as the specification of the empirical model is theoretically well founded. In the following, to simplify the matter, we use expressions like "impact on productivity" or "productivity effect", but always being aware of the fact that we cannot establish causal links. Finally, we indicate that all previous studies suffer from the same deficiency, as they also use cross-section data (estimates with data from a single cross-section).

## 6.2 Empirical results

Table 10 shows econometric estimates of different models we use to explain the relationship between specific innovation strategies and a firm's labour productivity (nominal value added per employee; full-time equivalents). Column 3 provides the results for the *full model*, which contains all categories of variables specified in the previous subsection (four sets of variables). The equations displayed in the columns 1 and 2 highlight some *partial* aspects related to the relative importance of the variables representing the firms' choice of specific innovation strategies and, respectively, their industry affiliation. In column 4, we present, for the Swiss economy, estimates based on the model specification employed by Frenz and Lambert (2012) and Sanchez (2014). In so doing, we are able to compare our results with those of previous studies.

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<sup>17</sup> In the following, we only refer to Frenz and Lambert (2012), as their 2009 paper is largely a first version of the more recent study.

*Model 1* (Table 10, column 1) includes, in addition to three time dummies, only the variables representing the firms' *innovation strategies*. We thus do not take into account that other variables also have an impact on labour productivity. It turns out that all strategies exert a statistically significant positive impact on labour productivity. However, the overall effect is rather weak, as indicated by the low value of the adjusted  $R^2$ . The *process/product-oriented strategy* (cluster 4) contributes least to productivity, and the effect of the *investment-based strategy* (cluster 2) is of "intermediate size". The impact on productivity is substantially larger in the case of the *science-based strategy* (cluster 1) and the *IT/process-oriented strategy* (cluster 3); to a lesser extent, this also is true in the case of the *IT/product-oriented strategy* (cluster 5). These results more or less mirror the differences between the five clusters with respect to the *average* labour productivity (see Table 9), which is not surprising as the equation does not include, with the exception of the time dummies, other variables than those capturing the innovation strategies.

In *model 2* (Table 10, column 2), we add 28 industry dummies (2-digit level). In so doing, we are able to compare the impact on productivity due to the firms' industry affiliation and the effect attributed to the firms' innovation strategies. The results of this comparison are only *tentative*, as we do not yet insert the variables representing the factor inputs and the structural firm characteristics (size and foreign ownership). The table shows that both categories of variables exert a statistically significant influence on productivity. The increase of productivity due to the choice of specific innovation strategies is quite similar to the corresponding impact in model 1 that does not include any industry dummies. The productivity effect of the two sets of variables is thus more or less independent. A comparison of the adjusted  $R^2$  for model 1 and 2 shows that industry affiliation (joint effect of all industry dummies), by far, is more relevant for explaining firm performance than the five innovation strategies (adjusted  $R^2$  of 0.210 in model 2 vs. 0.024 in model 1). As the fit of model 2 is so much higher than that of model 1, this assessment is correct even if we take account of the fact that the industry dummies also capture the influence of explanatory variables not explicitly specified in the model.

Column 3 of Table 10 shows the results for *model 3*, which contains *all* (four) *categories of variables* specified in the previous subsection ("*full model*"). It turns out that the productivity effect of the firms' innovation strategies becomes very weak as soon as we insert the variables representing the production function (with physical capital intensity as the most influential variable) and the structural firm characteristics (firm size, foreign ownership). In this model, only the *IT/product-oriented strategy* (cluster 5) exerts a positive (but only weak) influence on labour productivity. We notice that the adjusted  $R^2$  of model 3 is much larger than that of model 2 (0.77 vs. 0.21). This result is not surprising as, from a theoretical point of view, the factor inputs are the most important determinants of a firm's labour productivity.

When we drop from the full model the variables "firm size" and "foreign ownership", which in the full model are highly significant with the expected positive sign, the adjusted  $R^2$  still is much larger than in the case of model 2. Again, only the *IT/product-oriented strategy* (cluster 5) yields a productivity premium, and this effect remains small, although it is somewhat larger than according to the estimates for the full model. Furthermore, reducing the full model by leaving out (a) the

industry dummies, and *alternatively*, (b) the five strategy variables shows again that the productivity effect of a firm's industry affiliation is much larger than that of the innovation strategies.

To get a correct assessment, it is necessary to take account of the *correlations* between the explanatory variables, as these may bias the model estimates. An inspection of the correlation matrix shows that only two variables correlate with other explanatory variables to an extent that they *potentially* distort the estimates of the full model. *Firstly*, there is a positive correlation between the *R&D intensity* and three of the innovation strategies (clusters 1, 2 and 4) as well as with human capital.<sup>18</sup> *Secondly*, we find that the *science-based strategy* (cluster 1) quite strongly correlates with the input of R&D and human capital, as well as with a few dummies representing the firms' affiliation to specific R&D intensive industries (e.g., chemicals/pharmaceuticals). Separate estimates of model 3, which take account of these correlations, indicate that the productivity effect of the *IT/product-oriented strategy* (cluster 5) is larger than shown in column 3 of the table. Moreover, the *science-based strategy* (cluster 1) also *tends* to raise a firm's labour productivity, but this effect is statistically not significant. *Physical capital intensity*, which, by far, is the most important explanatory variable, is *uncorrelated* with almost all other determinants of labour productivity. We only find some weak correlation with human capital intensity, foreign ownership and four of the 28 industry dummies. Separate estimates that take account of these correlations do not change the results reported above.

In view of the high relevance of the physical capital intensity for explaining firm performance, it is sensible to check the *robustness* of the results by using alternative specifications of this variable. To this end, we replace in model 3 (Table 10, column 3) the "capital to labour ratio" by the "capital to output ratio" and, alternatively, the "investment to labour ratio" (in the latter case, data are available only for 2005 and 2008). In the first specification (*capital to output ratio*), the coefficient of the physical capital intensity is highly significant, and the results for the rest of the model are very similar to those we get for the base model shown in Table 10. Among the variables representing the firms' innovation strategies, as before, only the *IT/product-oriented strategy* (cluster 5) is statistically significant. In the second specification (*investment to labour ratio*), we also find that the physical capital intensity, by far, is the most important variable for explaining productivity. In this case, we do not find a statistically significant productivity effect for any of the five strategy variables.

Altogether, the results of the additional estimates (not shown in Table 10) confirm that the impact of the firms' choice of specific innovation strategies on labour productivity is small. However, if we take account of the correlations between the explanatory variables, we get a slightly higher (but still weak) contribution to productivity in the case of two (out of the five) strategy variables, that is, the *IT/product-oriented strategy* and, though only *as a tendency*, the *science-based strategy*.

Table 10 (*about here*)

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<sup>18</sup> As the correlation between the R&D intensity and the two indicators of human capital is quite strong, the R&D variable is statistically insignificant in all models.

### 6.3 Comparison with earlier studies

We remind that Hollenstein (2003) also analyses the relationship between the firms' innovation strategies and labour productivity in a production function framework, however, based on a sample that only includes *services companies*. He finds that solely one out of five innovation strategies raises a firm's labour productivity (i.e., "*IT-oriented network-integrated developing firms*"). To allow a comparison with his results, we also estimate our model for the service sector only. In so doing, we obtain a statistically significant effect on productivity for the *IT/product-oriented strategy* (cluster 5). The results of the two studies are thus quite similar, although the innovation strategies identified in the two studies are not identical.

Frenz and Lambert (2012) and Sanchez (2014), as mentioned in subsection 6.1, apply a model to explain firm performance that contains three categories of explanatory variables: (a) the firms' innovation strategies, (b) some structural firm characteristics, and (c) industry/sector dummies.<sup>19</sup> Frenz and Lambert (2012), using data from fifteen OECD countries, identify for the majority of countries a statistically significant productivity effect for one or two (out of five) innovation strategies.<sup>20</sup> Based on data for US companies, Sanchez (2014) finds that each innovation strategy identified in a first step of the analysis raises labour productivity. However, this study may overestimate these effects, as the model only contains one sector dummy (manufacturing yes/no), whereas the other papers use 2-digit industry dummies. In sum, both studies find that the firms, on average, are in a position to gain a competitive edge by choosing a specific innovation strategy, as hypothesised in the strategic management literature.

However, the *specification of the models* used in the two studies is *not adequate*, as it does not account for the productivity effects of the classical factor inputs, which, according to the economic theory, are the most important explanatory variables. Therefore, to get a more reliable comparison with our results, we estimate for Switzerland a productivity model where we apply, as far as possible, the specification used by Frenz and Lambert (2012) and Sanchez (2014), respectively. We thus delete from our model the variables capturing the use of physical, human and R&D capital. Column 4 of Table 10 shows the estimate of this "reduced model" with the Swiss data. It turns out that, in this specification, *all* innovation strategies exert a statistically significant influence on firm productivity, which is fully in line with Sanchez (2014).<sup>21</sup> In contrast, as reported in the previous paragraph, Frenz and Lambert (2012) find that, in the majority of the countries they analyse, only one or two (out of five) innovation strategies raise a firm's productivity.

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<sup>19</sup> The two studies use "sales per employee" as a proxy for productivity, whereas we employ "value added per employee". As the sales share of intermediate inputs should not vary too much *within* industries, the estimates of models using the one or the other dependent variable are largely comparable, provided the explanatory variables include a similar *set of industry dummies*, which is the case in Frenz and Lambert (2012). In contrast, a comparison with Sanchez (2014) is more problematic, as the model of this study only contains a *sector dummy* (manufacturing yes/no).

<sup>20</sup> The estimates do not point to a consistent cross-country pattern as to which innovation strategies significantly affect firm performance.

<sup>21</sup> We get the same result when we use, in accordance with Sanchez (2014), only a sector dummy ("manufacturing yes/no") instead of 2-digit industry dummies.

We remind that, for Swiss firms, the positive productivity effect of the five innovation strategies disappears in the case of four (out of five) strategies as soon as we use the theoretically well-founded model 3 (full model) instead of the (theoretically unsatisfactory) reduced model excluding the factor input variables (see column 3 vs. 4 in Table 10). We do not see any reason why the same should not happen in estimates for other countries as well, if one would use a correctly specified model (i.e., a model including the factor inputs). Therefore, we conclude, by analogy, that the stronger effects of the innovation strategies identified by Sanchez (2014) for US companies, and, to a lesser extent, by Frenz and Lambert (2012) for eight (out of fifteen) OECD countries, in the first instance, reflect a misspecification of the empirical productivity model.

#### **6.4 Assessment of the results**

Altogether, the results imply that a firm's scope for improving its market position by choosing a specific innovation strategy, though it exists in some instances, is limited, not only in Switzerland but in other countries as well. In the Swiss case, we find a positive, but weak effect on labour productivity only for one (out of five) innovation strategy, i.e. the IT/product-oriented strategy. Taking account of the correlations between the explanatory variables, the same may be true, but only as a tendency, for the science-based strategy. However, other determinants of a firm's labour productivity are much more important, that is (a) the intensity of use of physical, human and R&D capital (with the largest effect in the case of physical capital), (b) some structural firm characteristics (firm size, foreign ownership), and, (c) industry affiliation. In the present context, the most important finding is the fact that the productivity effect of the industry dummies is much larger than that of the firm-specific innovation strategies.

The results seem to be consistent with the view that (innovation-related) structural factors at the industry level significantly restrict a firm's choice of *productivity-enhancing* innovation strategies. Nevertheless, there is some room for implementing specific strategies at firm level that provide a competitive edge, but, in general, it is rather limited as only one (or at most two) strategy yields a small productivity premium. The empirical results are thus primarily in line with the *technological regime approach*, whereas the evidence for the strategic management view of innovation is quite weak.

We remind that the empirical results with respect to the intra-industry heterogeneity of innovation strategies, presented in the previous section, primarily support the *strategic management view*. However, we also argued that the evidence with respect to the intra-industry heterogeneity might not be strong enough to reject the technological regime approach. Given the contradictory results we find in the present and the previous section, we conclude that the evidence does not allow to rejecting one of the two approaches. Moreover, we also are not able to assess the "relative strength" of the two concepts for explaining the firms' innovation behaviour. Against this background, we conclude that the two approaches are rather complements than substitutes.

## 7 Summary and conclusions

The aim of this paper is to provide new evidence with respect to the still unresolved question, whether a firm's innovation behaviour primarily reflects industry-specific characteristics (“*technological regime approach*”), or whether it is, in the first place, the outcome of firm-specific innovation strategies to create a competitive advantage (“*strategic management literature*”). To this end, we empirically investigate four topics.

*Firstly*, we identify a set of innovation strategies of firms (modes of innovation) based on a large number of innovation indicators using factor and cluster analysis. We then evaluate the economic plausibility of these strategies, drawing on the most important demand and supply side determinants of a firm's innovation activity as postulated in the economics of innovation. Such a theory-based assessment of the clusters identified by use of statistical methods is missing in (practically all) previous research. This first element of the analysis provides the basis for the further (more innovative) parts of the study. *Secondly*, we examine the dynamics of innovation strategies. To our knowledge, this is the first large-scale investigation of this topic. We use information on the frequency and the direction of the firms' switches from their initial to a new strategy between two points in time. The analysis provides a further check of the appropriateness of the modes of innovation identified in the first part of the study. *Thirdly*, we investigate the intra-industry heterogeneity of innovation modes for a large number of 4-digit NACE industries, which presumably are more or less homogeneous in terms of the firms' production activities. Previous studies, with one exception (see below), only use information at the 2-digit level. The analysis yields new evidence with respect to the relative merits of the strategic management concept of innovation and the technological regime approach. *Finally*, by identifying the relative importance of industry affiliation and innovation strategies as variables to explaining firm performance (productivity) we provide additional insights into the appropriateness of the two approaches. To this end, we econometrically estimate a production function, which includes, in addition to the classical production factors and some structural firm characteristics, a set of variables representing the firms' innovation strategies as well as 2-digit industry dummies. Surprisingly, previous studies dealing with this topic, with one exception (see below), do not account for the intensity of use of the production factors, which, according to theory and empirical research, are the most important explanatory variables in a productivity equation.

The study draws on *firm-level data* stemming from the Swiss Innovation Survey conducted every third year by the KOF Swiss Economic Institute (ETH Zurich) based on a stratified random sample of the entire business sector. We use pooled data collected in four waves of the survey that cover the period 1999 to 2008. The dataset contains about 5000 observations.

We may summarise the *results* of the empirical analysis as follows:

*Firstly*, based on a cluster analysis of a large number of innovation indicators, we identify five “modes of innovation” (innovation strategies). These are satisfactory not only in statistical terms but also from a theoretically point of view as each strategy shows a specific configuration of demand and supply side determinants of the firms' innovation performance. We distinguish (a) a science-

based strategy, (b) an investment-based strategy, (c) an IT/process-oriented strategy, (d) a process/product-oriented strategy, and (e) an IT/product-oriented strategy. On average, the companies pursuing strategy (a) or (e) are the most innovative ones (“high-profile innovators”), whereas those adhering to strategy (b) or (d) are the least innovative firms (“low-profile innovators”); companies choosing strategy (c) exhibit an intermediate innovation intensity (“medium-profile innovators”). Other researchers identify strategies similar to (a) and (b), but, quite remarkably, no one finds an IT-oriented strategy like (c) or (e). This may be due to a lack of data on IT-related innovation activities.

*Secondly*, we find that a high proportion of firms modifies their innovation strategy in the course of only three years. Apparently, important aspects of a company’s innovation-related environment (demand prospects, intensity of competition, technological opportunities, etc.) change quite quickly, and the firms seem to be able to switch rapidly to a more adequate strategy. It turns out that the science-based strategy (a), and, somewhat less pronounced, the two IT-related strategies (c) and (e), which are pursued by the most innovative firms, are the “net winners” from the shifts of strategies. In these cases, the number of firms attracted from other strategies (“inflows”) is larger than the number of firms switching to another strategy (“outflows”). The “net losers” of the shifts of strategies (i.e., “outflows” are larger than “inflows”) are the companies pursuing the least innovative strategy (d). The pattern of the dynamics of the firms’ innovation strategies is fully in line with the structural change required in a highly advanced economy such as the Swiss one. In this type of economy, the innovation content of the firms’ activities constantly has to be increased. The pattern of the dynamics of strategies we observe is thus highly plausible. These findings further confirm the adequacy of the five innovation modes identified in the first part of the study.

*Thirdly*, a large share of the 4-digit industries (which should be more or less homogenous in terms of their production activities) is characterised by a substantial degree of heterogeneity of innovation strategies (clusters). The proportion of industries appearing in at least four clusters (strategies) is very high, but we also find quite often a certain concentration on one or two strategies. Moreover, the pattern of the distribution of the firms over the five innovation modes, in many instances, is rather similar at the 4-digit and the corresponding 2-digit industry level, i.e., we observe the same peak (or the same two peaks) at the two levels of aggregation. Therefore, the evidence, though it primarily supports the “strategic management view” (heterogeneity hypothesis), may not be strong enough to reject the technological regime approach (homogeneity hypothesis). This assessment is only partly in line with the findings of the only study using highly disaggregated data, which clearly favours the heterogeneity hypothesis (Leiponen and Drejer 2007).

*Finally*, it turns out that the impact of the firms’ innovation strategies on labour productivity is weak, and, by far, smaller than the influence exerted by the industry affiliation. Only the IT/product-oriented strategy (and, as a tendency, the science-based strategy) provides a (small) productivity premium. These findings primarily support the “technological regime approach” (homogeneity hypothesis). The results are in line with the only methodologically convincing study (i.e., using a production function framework) that is available to date (Hollenstein 2003).

The evidence reported on in the last two paragraphs is contradictory. We interpret this finding as follows: The firms have a certain room of manoeuvre to implement a specific innovation strategy that reflects their particular capabilities. However, only one strategy (or perhaps two) really provide a competitive edge, as suggested by the “strategic management view”. As industry affiliation exerts a much stronger influence on productivity, we conclude, as postulated by the “technological regime approach”, that there are some (innovation-related) structural characteristics at the industry level (e.g. technological opportunities, appropriability conditions, market prospects), which restrict the strategic options of the individual company. Altogether, the results imply that the two perspectives on the firms’ innovation behaviour are complements rather than substitutes, whereas previous research, with the important exception of Peneder (2010), clearly prefers either the one or the other interpretation.

Each part of this study *adds to our knowledge* on the firms’ innovation behaviour, though not to the same extent. Firstly, we do not only identify a set of innovation strategies of firms but, what is neglected so far, we also provide a theory-based evaluation of their appropriateness using information on the determinants of innovation intensity. Secondly, we perform, what is new, a large-scale analysis of the dynamics of the firms’ innovation strategies, which also provides some insights into the structural change of the business sector as a whole. Thirdly, we deal with the intra-industry heterogeneity of innovation modes based on a large number of highly disaggregated industries (4-digit). In so doing, we are able to determine the degree of heterogeneity much more reliably than it is the case in previous research, which mostly uses 2-digit industry data. Fourthly, the study is practical the only one which investigates, based on a theoretically adequate model, the relative importance of the firms’ innovation strategy and their industry affiliation as determinants of firm performance. By combining the results of the third and the fourth part of the paper, we get new insights into the adequacy of the “strategic management concept”, and the “technological regime approach” as perspectives of the firms’ strategic behaviour with respect to innovation.

The study has a number of *limitations*. Firstly, the dataset only includes information up to 2008. In view of the distinct structural change of the economy in the course of the last decade (rapid technological change, globalisation of business activities, etc.), an analysis with more recent data might have provided additional insights. However, we could not go beyond 2008 as the questionnaire used in the Swiss Innovation Surveys was modified quite significantly since that time. Secondly, the investigation of the dynamics of the firms’ innovation strategies draws on unbalanced panel data, with the consequence that we could deal only with strategic switches taking place over a relatively short period. Thirdly, the analysis of the dynamics of innovation strategies is purely descriptive. Hence, research aiming to identify the factors determining a firm’s decision to switch from one to another innovation strategy would be an interesting field for future work. Fourthly, due to the cross-section nature of the data, the results with respect to the effect of a firm’s innovation strategy, respectively, its industry affiliation on firm performance have to be interpreted as conditional correlations rather than causal relationships. Nevertheless, as the model underlying the econometric analysis is theoretically well established (production function framework), we hold that it is possible to assess whether the empirical results are consistent with the “strategic management

view” or the “technological regime approach” of the firms’ innovation behaviour. Nevertheless, an econometric analysis of this topic based on longitudinal data would be highly welcome.

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**Table 1: Innovation indicators used in the factor analysis**

Innovation indicator	Measurement scale and value range	
<i>Input-oriented measures</i>		
Expenditures for		
- Research	Ordinal	1, ..., 5
- Development	Ordinal	1, ..., 5
- IT (hardware, software)	Ordinal	1, ..., 5
Innovation-related follow-up expenditures		
- In general	Ordinal	1, ..., 5
- Machinery and equipment	Ordinal	1, ..., 5
- Acquisition of external knowledge (consultancy, licenses, etc.)	Ordinal	1, ..., 5
- Training activities related to innovation activities and IT	Ordinal	1, ..., 5
- Expenditures for the introduction of innovative products on the market	Ordinal	1, ..., 5
<i>Output-oriented measures</i>		
Patent applications (no/yes)	Nominal	0, 1
Significance of product innovations		
- in technical terms	Ordinal	1, ..., 5
- in economic terms	Ordinal	1, ..., 5
Significance of process innovations		
- in technical terms	Ordinal	1, ..., 5
- in economic terms	Ordinal	1, ..., 5
<i>Market-oriented measures</i>		
Sales share of new or significantly improved products (%)	Metric	0, ..., 100
Cost reduction due to process innovations (no/yes)	Nominal	0, 1

**Table 2: Factor analysis of the innovation indicators**

Innovation indicator	Rotated factor pattern (varimax) <sup>a</sup>				
	F1	F2	F3	F4	F5
Significance of process innovations in economic terms	<b>0.88</b>	-0.01	0.11	0.03	0.13
Significance of process innovations in technical terms	<b>0.86</b>	-0.03	0.04	0.03	0.16
Cost-reduction due to process innovations	<b>0.60</b>	0.13	-0.04	0.17	-0.10
Expenditures for research	0.06	<b>0.80</b>	0.07	0.02	0.11
Expenditures for development	0.02	<b>0.78</b>	0.20	0.17	0.09
Patent applications	0.03	<b>0.63</b>	0.12	0.15	-0.16
Significance of product innovations in economic terms	0.03	0.09	<b>0.86</b>	0.13	-0.02
Significance of product innovations in technical terms	0.04	0.11	<b>0.84</b>	0.11	0.00
Sales share of new or significantly improved products	0.04	0.30	<b>0.45</b>	-0.10	0.12
Innovation-related follow-up expenditures for machinery and equipment	0.18	0.10	0.05	<b>0.80</b>	-0.01
Innovation-related follow-up expenditures in general	0.09	0.13	0.03	<b>0.73</b>	0.24
Expenditures for the introduction of innovative products on the market	-0.11	0.30	0.32	<b>0.44</b>	0.28
Acquisition of external knowledge (consultancy, licences, etc.)	-0.01	0.17	-0.00	0.09	<b>0.72</b>
Expenditures for IT (hardware and software)	0.15	-0.12	0.01	0.05	<b>0.71</b>
Follow-up expenditures for training activities related to innovation and IT	0.04	0.00	0.12	<b>0.46</b>	<b>0.59</b>
Number of observations					5645
Kaiser's overall measure of sampling adequacy (MSA)					0.71
Variance accounted for by the first five factors					0.60
Variance accounted for by each factor	3.39	1.99	1.53	1.20	0.96
Final communality estimate (total)					9.07
Root mean square off-diagonal residuals (RMSE)					0.078

<sup>a</sup> Factor values greater than 0.40 are in bold.

**Table 3: Cluster analysis <sup>a</sup>**

Factors	Cluster 1 <i>Science-based strategy</i> (N = 1021)	Cluster 2 <i>Investment-based strategy</i> (N = 1397)	Cluster 3 <i>IT/process-oriented strategy</i> (N = 802)	Cluster 4 <i>Process/product-oriented strategy</i> (N = 1555)	Cluster 5 <i>IT/product-oriented strategy</i> (N = 870)
F1: Process-orientation	-0.32	-0.13	0.29	0.59	-0.74
F2: Science-orientation	1.41	-0.20	-0.07	-0.42	-0.52
F3: Product-orientation	0.15	-0.55	-1.04	0.52	0.74
F4: Investment-orientation	-0.26	0.81	-0.38	-0.51	0.28
F5: IT-orientation	-0.20	-0.53	1.16	-0.45	0.84
<b>Statistics</b>					
Number of observations	5645				
Pseudo-F	779***				
Expected overall R <sup>2</sup>	0.44				

<sup>a</sup>The cluster analysis relies on the factor analysis which identifies five factors (F1 to F5); see Table 2.

**Table 4: Indicators used to characterise and evaluate the clusters**

Indicator	Measurement scale and value range	
<i>Innovative activity</i>		
- Innovation indicators used in the cluster analysis (see Table 1)		
<i>Objectives of innovation</i>		
- Relevance of several product-related objectives	Ordinal	1, ..., 5
- Relevance of several process-related objectives	Ordinal	1, ..., 5
<i>Determinants of innovation</i>		
Demand side		
- Medium-run demand prospects in the product market	Ordinal	1, ..., 5
- Intensity of price competition	Ordinal	1, ..., 5
- Intensity of non-price competition	Ordinal	1, ..., 5
- Less than 5 principal competitors at world level (no/yes)	Nominal	0, 1
Supply side		
- Innovation opportunities in the relevant fields of activities	Ordinal	1, ..., 5
- Appropriability of knowledge	Ordinal	1, ..., 5
- Share of employees with tertiary qualifications (%)	Metric	0, ..., 100
<i>Knowledge network</i>		
Sources of knowledge		
- Intensity of use of 14 types of external knowledge sources	Ordinal	1, ..., 5
R&D contracts		
- Domestic contractor (no/yes)	Nominal	0, 1
- Foreign contractor (no/yes)	Nominal	0, 1
R&D co-operation		
- Domestic partner (no/yes)	Nominal	0, 1
- Foreign partner (no/yes)	Nominal	0, 1
<i>Structural characteristics of the firm</i>		
Firm size		
- Number of employees (median)	Metric	1 or more
- Share of firms (%) by six size classes (no. of employees):	Metric	0, ..., 100
5-19, 20-49, 50-99, 100-249, 250-499, 500 or more		
Firm age		
- Less than 15 years old (no/yes)	Nominal	0, 1
Export intensity		
- Share of firms by export to sales ratio (%):	Metric	0, , 100
0-1, 2-20, 21-60, 61-100 (%):		

**Table 5: Movements of firms between clusters over a three-year period <sup>a, b</sup>**

	<b>Number of firms moving between the clusters</b>					Total
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	
Cluster 1		55	22	48	46	171
Cluster 2	67		49	79	51	246
Cluster 3	22	34		56	31	143
Cluster 4	66	117	51		69	303
Cluster 5	36	47	34	69		186
Total	191	253	156	252	197	1049

<sup>a</sup> The diagonal remains empty as we do not consider, at this stage of the analysis, the firms that stick to their current strategy for reasons mentioned in the text.

<sup>b</sup> Cluster 1: science-based strategy; cluster 2: investment-based strategy; cluster 3: IT/process-oriented strategy; cluster 4: process/product-oriented strategy; cluster 5: IT/product-oriented strategy.

**Table 6a: Ratio between inflows from and outflows to other clusters (columns)**

	<i>Ratio of inflows from and outflows to other clusters (columns)</i>				
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Cluster 1		0.82	1.00	0.73	1.28
Cluster 2	1.22		1.44	0.68	1.09
Cluster 3	1.00	0.69		1.10	0.91
Cluster 4	1.38	1.48	0.91		1.00
Cluster 5	0.78	0.92	1.10	1.00	
Total	1.12	1.03	1.09	0.83	1.06

<sup>a</sup> The diagonal remains empty as we do not consider, at this stage of the analysis, the firms that stick to their current strategy for reasons mentioned in the text.

**Table 6b: Qualitative assessment of the attractiveness of innovation modes**

Innovation strategy	Assessment based on the ratios shown in Table 6a <sup>a, b, c</sup>				
	Science-based	Investment-based	IT/process-oriented	Process/product-oriented	IT/product-oriented
Science-based	///	-		--	++
Investment-based	++	///	+++	---	
IT/process-oriented		---	///	+	
Process/product-oriented	+++	+++		///	
IT/product-oriented	--		+		///
Total	++		+	--	+

<sup>a</sup> The slashes on the diagonal mean that we do not consider the firms that stick to their current strategy for reasons mentioned in the text

<sup>b</sup> Cells with three positive or negative signs (+++/---) indicate that the deviation from unity (where inflows and outflows are equal) amounts to 30% or more. Two signs (++/--) represent discrepancies of more than 20% (but less than 30%), whereas one sign (+/-) stands for differences of 10% to 20%. Empty cells reflect small deviations from unity (less than 10%). The slashes on the diagonal (///) represent the fact that we do not consider the firms that stick to their initial strategy.

<sup>c</sup> For the “total balance of inflows to outflows” of the five clusters (*last row*), we use less restrictive definitions of the number of signs, as the deviation from unity of the individual clusters (row 1 to 5) tend to even out. Therefore, for the *total* of the strategic moves, two signs (++/--) indicate differences from unity of more than 10%, whereas one sign (+/-) stands for divergences of 5% to 10%.

**Table 7: Intra-industry distribution of firms by cluster**

Sector / industry	Science-based	Investment-based	IT/process-oriented	Process/product-oriented	IT/product-oriented	Total
<b>Low-tech manufacturing</b>	16.3	<b>35.8</b>	11.1	28.2	8.6	100
Food, beverages, tobacco	18.5	39.9	7.7	23.9	10.0	100
Textiles	25.5	25.5	2.0	35.7	11.2	100
Clothing, leather	20.0	20.0	3.3	43.4	13.3	100
Wood products	15.0	44.0	11.0	19.0	11.0	100
Paper	12.8	38.4	11.6	31.4	5.8	100
Printing, publishing	5.9	23.7	30.2	30.7	9.5	100
Non-metallic minerals	20.6	39.2	5.9	28.4	5.9	100
Metals	17.4	47.8	8.7	17.4	8.7	100
Metal products	14.2	39.4	7.9	32.5	6.0	100
Watchmaking	26.4	36.3	5.5	23.6	8.2	100
Other manufacturing	21.7	26.1	5.2	35.7	11.3	100
Electricity, gas, water	3.9	36.4	36.4	14.2	9.1	100
<b>High-tech manufacturing</b>	<b>33.6</b>	21.6	4.5	25.3	15.0	100
Pharmaceuticals, chemicals	40.2	19.2	4.2	26.8	9.6	100
Rubber, plastics	16.8	39.1	7.0	22.4	14.7	100
Non-electrical machinery	34.3	18.5	4.9	25.5	16.8	100
Electrical machinery	32.0	34.3	1.7	23.4	8.6	100
Electronics, instruments	35.5	16.4	4.6	25.8	17.7	100
Transport equipment	26.5	20.4	4.1	24.5	24.5	100
<b>Construction</b>	6.1	<b>34.6</b>	20.3	27.1	11.9	100
<b>Knowledge-intensive services</b>	9.2	9.1	<b>33.5</b>	26.5	21.7	100
Banking, insurance	3.0	7.3	39.0	29.0	21.7	100
R&D, IT, technical services	25.8	4.8	11.3	21.0	37.1	100
Other business services	8.2	12.0	37.8	26.3	15.7	100
Telecommunication	18.2	27.2	18.2	27.2	9.2	100
<b>Other services</b>	6.1	22.1	19.8	<b>29.0</b>	23.0	100
Wholesale trade	8.3	16.1	18.9	27.2	29.5	100
Retail trade	5.7	24.1	18.9	26.8	24.5	100
Hotels, restaurants	2.6	27.5	13.7	41.8	14.4	100
Transport, storage, logistics	6.0	28.0	24.5	23.5	18.0	100
Real estate, renting	5.3	10.5	52.6	21.1	10.5	100
Personal services	0.0	22.2	14.8	44.5	18.5	100
<b>Total</b>	18.3	<b>25.0</b>	14.3	<b>27.1</b>	15.3	100

**Table 8: Relationship between innovation modes (clusters) and industry affiliation**  
(4-digit NACE classification) <sup>a</sup>

	Switzerland <sup>b</sup>	Finland <sup>c</sup>
1.A: Share of industries ( <i>at least 8 firms</i> ) without a dominating cluster (Switzerland 153 industries; Finland: 21 industries)	71%	61%
1.B: Share of industries ( <i>at least 10 firms</i> ) without a dominating cluster (Switzerland: 126 industries; Finland: 14 industries)	78%	80%
2.A: Share of industries ( <i>at least 8 firms</i> ) with <i>clearly specified activities</i> without a dominating cluster (Switzerland only: 128 industries)	69%	-
2.B: Share of industries ( <i>at least 10 firms</i> ) with <i>clearly specified activities</i> without a dominating cluster (Switzerland only: 105 industries)	75%	-
<i>Industries (at least 8 firms):</i> (Switzerland: 153 industries; Finland: 21 industries)		
3.A: Share of industries appearing in <i>all 5 clusters</i>	59%	-
3.B: Share of industries appearing in <i>at least 4 out of the 5 clusters</i>	88%	63%
4. <i>Number of clusters</i> with firms from at least 75% of the industries	5 (out of 5)	3 (out of 5)

<sup>a</sup> A cluster is defined as dominating if 50% or more firms are in *one* cluster.

<sup>b</sup> The figures for *Switzerland* are calculated from *Table A.3* in the appendix. The values in row 1.A and 1.B as well as those in row 3.A, 3.B and 4 are based on *part A and B* of that table, whereas we used only part A of the table for calculating the values shown in row 2.A and 2.B.

<sup>c</sup> The data for *Finland* stem from *Table 6* of Leiponen and Drejer (2007) and from own calculations based on *Table A1* in the appendix A of the Finnish study.

**Table 9: Variables used to estimate a firm's labour productivity by cluster**

	Science-based	Investment-based	IT/process-oriented	Process/product-oriented	IT/product-oriented	Total sample
	Cluster means					Mean
<i>Dependent variable</i>						
Labour productivity ( <i>nominal value added per employee, 1000 CHF</i> )	176	157	187	161	172	168
<i>Independent variables</i>						
Factor input						
- Capital to labour ratio (1000 CHF)	86	74	95	77	83	81
- <i>Alternative measures</i>						
- Capital to output ratio (%)	43	41	43	42	43	42
- Investment to labour ratio (1000 CHF) <sup>a</sup>	16	19	19	15	16	17
- Employment share of academics (%)	9.5	3.7	7.4	5.5	5.9	6.1
- Employment share of other tertiary qualifications (%)	26	15	23	19	22	20
- R&D expenditures per employee (%)	12	4.1	3.9	5.0	5.7	5.9
Cluster affiliation						
- Share of firms by cluster (%)	18	25	14	28	15	100
Firm size (number of employees)	440	389	456	293	213	355
Foreign-owned firm (%)	22	14	10	16	19	16
Sector affiliation (share of firms by sector, %)						
- Low-tech manufacturing	26	40	17	28	15	27
- High-tech manufacturing	59	31	18	33	33	36
- Construction	2	8	8	6	4	6
- Knowledge-intensive services	7	5	31	13	19	13
- Other (commercial) services	6	16	26	20	28	18

<sup>a</sup> The *investment to labour ratio* is the mean of the years 2005 and 2008 (no data for 1999 and 2002).

**Table 10: Relationship between innovation strategies and labour productivity (log) <sup>a</sup>**  
(Pooled data 1999, 2002, 2005 and 2008; OLS estimation)

Explanatory variable	Model 1	Model 2	Model 3	Model 4
<b>Clusters</b>				
Science-based strategy	.028*** (.01)	.031*** (.01)	.001 (.00)	.025*** (.01)
Investment-based strategy	.021*** (.01)	.021*** (.01)	.003 (.00)	.017*** (.01)
IT/process-oriented strategy	.026*** (.01)	.020*** (.01)	-.002 (.00)	.019*** (.01)
Process/product-oriented strategy	.015** (.01)	.019*** (.01)	-.000 (.00)	.015*** (.01)
IT/product-oriented strategy	.024*** (.01)	.014** (.01)	.007* (.00)	.014** (.01)
<b>Factor input</b>				
Capital to labour-ratio (log)	//	//	.378*** (.00)	//
Share of academics (log)	//	//	.019*** (.00)	//
Share of other tertiary qualifications (log)	//	//	.022*** (.00)	//
R&D expenditures per employee (log)	//	//	-.002 (.00)	//
<b>Structural firm characteristics</b>				
Number of employees (log)	//	//	.018*** (.00)	.018*** (.00)
Foreign-owned firm (yes/no)	//	//	.061*** (.01)	.186*** (.02)
<b>Industry affiliation</b>				
28 industry dummies (2-digit)	//	Yes	Yes	Yes
<b>Time dummies</b>				
3 year dummies with 1999 as reference group	Yes	Yes	Yes	Yes
<b>Statistics</b>				
Number of observations	4964	4964	4964	4964
F-value	16***	38***	388***	41***
Adjusted R2	.024	.210	.766	.235

<sup>a</sup> The estimates of the intercept are throughout omitted. The significance of the parameters is indicated with \*\*\*, \*\* and \* resp. representing the 1%, 5% and 10%-level with robust standard errors in brackets.

## APPENDIX

**Table A.1: Composition of the final sample by industry**

Sector / Industry	% of firms
<i>Low-tech manufacturing</i>	29.7
Food, beverages, tobacco	4.9
Textiles	1.8
Clothing, leather	0.6
Wood products	1.9
Paper	1.5
Printing, publishing	3.1
Non-metallic minerals	1.9
Metals	1.2
Metal products	7.0
Watchmaking	2.2
Other manufacturing	2.2
Electricity, gas ,water	1.4
<i>High-tech manufacturing</i>	31.2
Pharmaceuticals, chemicals	5.0
Rubber, plastics	2.6
Non-electrical machinery	11.8
Electrical machinery	3.3
Electronics, instruments	7.5
Transport equipment	1.0
<i>Construction</i>	5.6
<i>Knowledge-intensive services</i>	14.5
Banking, insurance	5.8
R&D, IT, technical services	2.6
Other business services	5.9
Telecommunication	0.2
<i>Other services</i>	19.0
Wholesale trade	6.9
Retail trade	4.4
Hotels, restaurants	3.0
Transport, storage, logistics	3.7
Real estate, renting	0.4
Personal services	0.6
Total	100

**Table A.2a: Innovative activities of firms by cluster<sup>a</sup>**

Innovation indicators	Science-based	Investment-based	IT/process-oriented	Process/product-	IT/product-oriented	Total
<i>Input-oriented measures</i>						
Expenditures for						
- Research	35	2	7	1	2	8
- Development	66	21	21	17	23	28
- IT (hardware, software)	12	13	57	14	46	24
Follow-up investments						
- In general	21	36	21	10	30	23
- Machinery and equipment	22	53	17	15	29	28
- Acquisition of external knowledge	5	1	25	1	16	7
- Training	19	23	40	13	54	27
- Market introduction of innovations	38	28	20	15	52	29
<i>Output-oriented measures</i>						
Significance of innovations in technical terms						
- Product	53	22	11	51	64	41
- Process	18	21	39	43	20	29
Significance of innovations in economic terms						
- Product	40	20	9	47	58	35
- Process	19	20	34	44	18	28
Patent application (% yes)	66	21	7	12	7	23
<i>Market-oriented measures</i>						
Sales share of new or highly improved products (%)	41	19	21	32	38	30
Cost reduction due to process innovations (% yes)	32	42	40	48	12	37

<sup>a</sup> If not otherwise specified, the table shows for each cluster and the total sample the percentage share of firms with score 4 or 5 on a five-point ordinal scale (for definition see Table 1). For example, 35% of the firms in cluster 1 spend much or very much on research.

**Table A.2b: Objectives of innovation activity of firms by cluster <sup>a</sup>**

Innovation objectives	Science-based	Investment-based	IT/process-oriented	Process/product-	IT/product-oriented	Total
<i>Product innovation</i>						
- Maintaining/increasing market shares	78	55	42	57	73	61
- Replacing mature products	40	26	19	26	42	30
- Enlarging range of products	55	41	36	43	61	47
- Accessing new regional markets	32	28	22	27	39	29
- Improving product quality	52	36	39	41	60	44
- Developing environmentally friendly products	26	19	14	15	22	19
<i>Process innovation</i>						
- Increasing flexibility of the production process	39	47	54	47	43	46
- Shortening production time	37	41	39	34	26	36
- Re-organisation of business processes	20	21	49	23	30	26
- Reducing need for stockholding	22	21	18	18	15	19
- Reducing labour costs	22	31	29	27	20	26
- Reducing material costs	24	18	16	16	15	18
- Reducing energy costs	14	15	12	12	10	13
- Reducing damage to the environment	13	16	15	14	10	14
<i>Aggregate objectives (factor analysis: 3 factors)</i>						
- Product and market development	.32	-.16	-.36	-.12	.42	0
- Re-organisation of business processes	-.13	.04	.28	-.01	-.12	0
- Reduction of production costs	.12	.07	-.11	-.02	-.13	0

<sup>a</sup> The upper part of the table shows for every objective of innovation the share of firms with score 4 or 5 on a five-point ordinal scale. For example, “maintaining/increasing market shares” is an important or a very objective for 78% of the firms of cluster 1. The sign of the aggregate variables (factors) shown in last three rows indicates whether the corresponding “bundle of innovation objectives” is more/less relevant than in the whole economy (in which case the factor value is zero).

**Table A.2c: Determinants of the innovation performance of firms by cluster <sup>a</sup>**

Determinants of innovation	Science-based	Investment-based	IT/process-oriented	Process/product-oriented	IT/product-oriented	Total
<b>Demand side</b>						
- Demand prospects	58	48	50	55	53	53
- Intensity of price competition	69	73	72	72	71	71
- Intensity of non-price competition	43	37	36	40	50	41
- Less than <i>five</i> principal competitors (%)	36	27	27	28	28	29
<b>Supply side</b>						
- Technological/innovation opportunities	42	25	29	27	36	31
- Appropriability of knowledge	19	8.9	7.4	9.3	8.5	11
- Highly qualified labour (%)						
a) Employment share of academics (%)	10	3.8	7.9	5.8	6.0	6.4
b) Employment share of all tertiary qualifications (%)	27	16	24	20	23	21

<sup>a</sup> If not otherwise specified, the table shows for each cluster and the total sample the percentage share of firms with score 4 or 5 on a five-point ordinal scale (for definition see Table 4). For example, 58% of the firms in Cluster 1 have favourable or very favourable demand prospects.

**Table A.2d: The knowledge network of firms by cluster <sup>a</sup>**

Knowledge sources / innovation network	Science- based	Investment- based	IT/process- oriented	Process/ product- oriented	IT/product- oriented	Total
Sources of knowledge						
- Users	54	46	42	45	52	47
- Suppliers of materials and components	40	41	35	38	46	40
- Suppliers of software	12	24	24	17	21	20
- Suppliers of machinery and equipment	13	14	41	20	35	23
- Competitors	28	29	34	26	34	29
- Other firms of the same group	29	20	21	19	22	22
- Universities	34	16	18	15	19	20
- Other research institutions	19	9	9	8	9	11
- Consultants	10	8	19	8	12	11
- Technology transfer organisations	7	4	8	4	8	6
- Patent documents	19	8	3	5	6	8
- Fairs and exhibitions	40	34	27	30	40	34
- Scientific and trade journals, conferences	41	33	35	31	42	36
- Computer networks	23	15	28	19	32	22
Out-contracting of R&D						
- At least one domestic contractor (%)	55	34	28	33	26	35
- At least one foreign contractor (%)	29	12	10	11	12	15
R&D co-operation						
- At least one domestic co-operation partner (%)	37	18	17	16	16	20
- At least one foreign co-operation partner (%)	33	14	11	13	13	17

<sup>a</sup> If not otherwise specified, the table shows for each cluster and the total sample the percentage share of firms with score 4 or 5 on a five-point ordinal scale (for definition see Table 4). For example, in cluster 1, users are important or very important as a source of knowledge for 54% of the firms.

**Table A.2e: Selected structural characters of firms by cluster**

Structural characteristics	Science-based	Investment-based	IT/process-oriented	Process/product	IT/product-oriented	Total
Number of employees						
- Mean	398	351	433	272	191	325
- Median	108	81	69	49	43	67
Share of firms by size class (employees), %						
- 5-19	16	17	18	24	25	20
- 20-49	15	20	23	25	27	22
- 50-99	16	19	15	18	15	17
- 100-249	27	24	19	19	17	21
- 250-499	14	12	12	8	8	11
- 500 or more	12	8	13	6	8	9
Share of firms that are less than 15 years old (%)	14	11	14	15	17	14
Share of firms by export to sales ratio (%)						
- 0-1	18	41	63	43	49	42
- 2-20	15	21	16	20	18	18
- 21-60	19	18	12	17	16	17
- 61-100	48	20	9	20	17	23

**Table A.3: Intra-industry distribution of firms by cluster <sup>a</sup>**  
*(4-digit classification; 153 industries with at least 8 firms)*

NACE Rev. 1	Description	N	Share (%) of firms by cluster <sup>a</sup>				
			1	2	3	4	5
<b>A. Industries with <i>clearly specified</i> activities</b>							
1513	Production of meat and poultry meat products	17	29	41	6	12	12
1551	Operation of dairies and cheese making	23	30	43	0	17	9
1561	Manufacture of grain mill products	8	38	13	0	<b>50</b>	0
1571	Manufacture of prepared foods for farm animals	8	13	25	13	25	25
1581	Manufacturing of bread, fresh pastry goods and cakes	25	8	<b>56</b>	12	20	4
1582	Manufacture of rusks and biscuits and preserved pastry goods and cakes	8	25	25	13	25	13
1584	Manufacture of cocoa; chocolate and sugar confectionary	29	21	38	10	24	7
1587	Manufacture of condiments and seasonings	8	13	<b>50</b>	0	25	13
1596	Manufacture of beer	10	30	20	20	10	20
1598	Manufacture of mineral waters soft drinks	9	22	<b>56</b>	0	22	0
1730	Finishing of textiles	13	15	31	0	38	15
1740	Manufacture of made-up textile articles (except apparel)	8	<b>50</b>	13	0	25	13
2010	Sawmilling and planing of wood; impregnation of wood	17	6	<b>82</b>	0	12	0
2020	Manufacture of veneer sheets; manufacture of plywood	9	33	<b>56</b>	11	0	0
2030	Manufacture of builders' carpentry and joinery	66	12	33	15	24	15
2112	Manufacture of paper and paperboard	8	<b>50</b>	25	13	13	0
2121	Manufacture of corrugated paper(board) and of containers of (paper)board	32	3	47	16	25	9
2123	Manufacture of paper stationary	15	13	20	13	<b>53</b>	0

*Table A.3 (continued)*

Table A.3 (continued)

2211	Publishing of books	9	11	0	33	22	33
2212	Publishing of newspapers	23	0	39	13	35	13
2220	Printing and service activities related to printing (except 2222)	31	6	26	23	42	3
2221	Printing of newspapers	11	0	18	<b>55</b>	27	0
2412	Manufacture of dyes and pigments	9	<b>67</b>	22	0	11	0
2414	Manufacture of organic basic chemicals (excl. other 4-digits of 241)	9	<b>56</b>	0	11	33	0
2416	Manufacture of plastics in primary forms	17	<b>53</b>	18	6	24	0
2420	Manufacture of pesticides and other agro-chemical products	9	<b>67</b>	0	11	22	0
2430	Manufacture of paints, varnishes and similar coatings, printing ink, mastics	48	31	27	2	31	8
2441	Manufacture of basic pharmaceutical products	13	15	23	8	31	23
2442	Manufacture of pharmaceutical preparations	62	45	19	3	21	11
2451	Manufacture of soap and detergents, cleaning and polishing preparations	10	30	0	10	30	30
2452	Manufacture of perfumes and toilet preparations	22	<b>55</b>	0	5	32	9
2521	Manufacture of plastic plates, sheets, tubes and profiles	15	40	27	0	7	27
2522	Manufacture of plastic packaging goods	32	16	47	9	16	13
2523	Manufacture of builders' ware of plastic	21	24	43	0	19	14
2661	Manufacture of concrete products for construction purposes	17	12	47	6	29	6
2670	Cutting, shaping and finishing of ornamental and building stone	16	6	31	13	44	6
2741	Precious metals production	10	40	40	10	10	0
2751	Casting of iron	8	25	25	0	<b>50</b>	0
2753	Casting of light metals	16	13	<b>50</b>	19	13	6
2811	Manufacture of metal structures and parts of metal structures	53	9	43	11	28	8
2812	Manufacture of builders' carpentry and joinery of metal	27	22	33	0	37	7

Table A.3 (continued)

2822	Manufacture of central heating radiators and boilers	11	9	27	9	36	18
2840	Forging, pressing, stamping and roll forming of metal; powder metallurgy	27	7	37	4	48	4
2851	Treatment and coating of metals	44	20	32	2	41	5
2862	Manufacture of tools	50	18	34	10	26	12
2863	Manufacture of locks and hinges	14	14	<b>57</b>	7	21	0
2873	Manufacture of wire products	13	23	23	23	8	23
2874	Manufacture of fasteners, screw machine products, chain and springs	19	21	42	5	32	0
2911	Manufacture of engines and turbines, except aircraft, vehicle, cycle engines	9	22	22	11	22	22
2912	Manufacture of pumps and compressors	20	<b>60</b>	15	0	20	5
2913	Manufacture of taps and valves	25	36	28	4	20	12
2914	Manufacture of bearings, gears, gearing and driving elements	28	25	<b>50</b>	4	14	7
2921	Manufacture of furnaces and furnace burners	14	29	14	7	29	21
2922	Manufacture of lifting and handling equipment	38	24	18	8	34	16
2923	Manufacture of non-domestic cooling and ventilation equipment	34	24	24	3	26	24
2932	Manufacture of agricultural and forestry machinery (excl. tractors)	17	18	12	0	<b>53</b>	18
2940	Manufacture of machine tools	124	35	15	6	23	20
2952	Manufacture of machinery for mining, quarrying and construction	14	14	29	7	21	29
2953	Manufacture of machinery for food, beverage and tobacco processing	26	38	23	4	23	12
2954	Manufacture of machinery for textile, apparel and leather production	30	<b>73</b>	10	0	10	7
2971	Manufacture of electric domestic appliances	21	48	19	14	10	10
3002	Manufacture of computers and other information processing equipment	17	18	6	6	<b>53</b>	18
3110	Manufacture of electrical motors, generators and transformers	43	37	26	5	16	16
3120	Manufacture of electricity distribution and control apparatus	47	34	49	0	13	4
3130	Manufacture of insulated wire and cable	17	18	<b>53</b>	0	29	0

Table A.3 continued

Table A.3 continued

3140	Manufacture of accumulators, primary cells and primary batteries	8	<b>62</b>	38	0	0	0
3150	Manufacture of lighting equipment and electric lamps	17	18	24	0	41	18
3210	Manufacture of electronic valves, tubes and other electronic components	77	32	22	8	31	6
3220	Manufacture of TV and radio transmitters; apparatus for telephony/telegraphy	25	40	8	0	28	24
3310	Manufacture of medical and surgical equipment and orthopaedic appliances	84	36	18	6	19	21
3320	Manufacture of instruments and appliances for measuring, testing, etc.	125	42	14	3	26	14
3330	Manufacture of industrial process control equipment	26	31	8	0	27	35
3340	Manufacture of optical instruments and photographic equipment	25	20	36	4	12	28
3350	Manufacture of watches and clocks	101	27	36	5	24	9
3420	Manufacture of bodies for motor vehicles; manufacture of (semi-)trailers	9	22	22	0	22	33
3520	Manufacture of railway and tramway locomotives and rolling stocks	8	<b>50</b>	13	0	25	13
3530	Manufacture of aircraft and spacecraft	17	24	18	12	24	24
3611	Manufacture of chairs and seats	9	44	33	0	11	11
3612	Manufacture of office and shop furniture	17	29	24	18	24	6
3613	Manufacture of kitchen furniture	16	13	31	13	31	13
3614	Manufacture of furniture (other than 3611, 3612, 3613, 3615)	22	14	18	0	<b>59</b>	9
3662	Manufacture of brooms and brushes	8	13	38	0	<b>50</b>	0
4010	Production and distribution of electricity	69	4	35	36	14	10
4523	Construction of motorways, roads, airfields and sport facilities	16	13	<b>56</b>	0	25	6
4531	Installation of electrical wiring and fittings	34	9	15	26	32	18
4533	Plumbing; installation of heating and ventilation/air conditioning	23	17	26	13	30	13
4540	Sale, maintenance and repair of motorcycles and related parts/accessories	18	6	33	11	39	11
4544	Painting and glazing	21	5	24	33	19	19

Table A.3 (continued)

Table A.3 (continued)

5010	Sale of motor vehicles	14	7	7	0	36	<b>50</b>
5020	Maintenance and repair of motor vehicles	33	0	27	12	30	30
5134	Wholesale with alcoholic and other beverages	17	0	12	18	29	41
5143	Wholesale of electrical household appliances and radio and TV goods	17	18	18	12	24	29
5146	Wholesale of pharmaceutical goods	13	8	0	23	15	<b>54</b>
5152	Wholesale of metals and metal ores	9	0	33	44	11	11
5153	Wholesale of wood, construction materials and sanitary equipment	13	8	15	15	38	23
5154	Wholesale of hardware, plumbing and heating equipment and supplies	17	18	12	41	18	12
5155	Wholesale of chemical products	8	25	25	13	13	25
5184/5	Wholesale of computers and related products, software, other office machinery	12	0	25	42	0	33
5211	Retail sales in non-specialised stores (food/beverages/tobacco predominating)	12	0	<b>50</b>	25	25	0
5224	Retail sale of bread, cakes, flour confectionery and sugar confectionary	46	9	35	9	26	22
5231	Dispensing chemist	11	0	0	18	18	<b>64</b>
5242	Retail sale of clothing	14	7	21	43	7	21
5245	Retail sale of electrical household appliances and radio and television goods	19	11	5	32	42	11
5246	Retail sale of hardware, paints and glass	10	0	30	10	0	<b>60</b>
5511	Hotels	89	2	29	15	37	17
5530	Restaurants	39	5	33	10	41	10
6010	Transport via railways	19	0	42	42	16	0
6021	Scheduled passenger land transport (other than railways)	39	13	31	23	15	18
6024	Freight transport by road	49	2	35	16	33	14
6330	Activities of travel agencies and tour operators; tourist assistant activities	21	5	10	38	19	29

Table A.3 (continued)

Table A.3 (continued)

6420	Telecommunications	9	33	0	22	11	33
6512a	Monetary intermediation (except central banking and 6512b,c,d)	20	0	5	30	35	30
6512b	Cantonal banks	38	5	3	<b>53</b>	16	24
6512c	Saving and loan associations	64	2	16	28	33	22
6512d	Universal banks and private banking	65	6	5	34	35	20
6601/3	Life and non-life insurance (excl. pension funds and social security)	68	1	9	<b>51</b>	26	12
6720	Activities auxiliary to insurance and pension funding	20	10	10	25	30	25
7032	Management of real estates (on a fee or contract basis)	12	8	8	<b>50</b>	25	8
7220	Publishing of software, software consultancy and supply	75	12	4	16	23	45
7310	Research and experimental development on natural sciences and engineering	31	<b>65</b>	10	3	13	10
7411	Legal activities	10	10	10	30	30	20
7412	Accounting, book-keeping and auditing activities; tax consultancy	23	4	9	43	26	17
7414	Business and management consultancy activities	23	0	13	35	35	17
7420	Architectural and engineering activities and related technical consultancy	139	10	12	37	27	15
7430	Technical testing and analysis	10	0	20	<b>50</b>	20	10
7440	Advertising	9	0	0	<b>56</b>	22	22
7470	Industrial cleaning	15	7	13	47	20	13
9301	Washing and dry-cleaning of textile and fur products	22	0	27	18	41	14
<b>A. Industries with <i>not clearly specified activities</i> (general activities; activities n.e.c.)</b>							
1533	Processing and preserving of food and vegetables n.e.c.	8	13	25	13	25	25
1589	Manufacturing of other food products n.e.c.	25	16	32	8	40	4
1750	Manufacturing of other textiles n.e.c.	31	29	23	3	32	13

Table A.3 (continued)

Table A.3 (continued)

2125	Manufacture of other articles of paper and paperboard n.e.c.	16	19	44	6	31	0
2222	Printing n.e.c.	64	6	19	41	28	6
2466	Manufacture of other chemical products n.e.c.	24	38	21	8	33	0
2513	Manufacture of other rubber products	8	0	<b>50</b>	25	25	0
2524	Manufacture of other plastic products	50	14	34	8	32	12
2852	General mechanical engineering	53	13	28	11	42	6
2875	Manufacture of other fabricated metal products n.e.c.	32	6	<b>56</b>	9	28	0
2900	Manufacture of machinery n.e.c.	15	20	20	7	47	7
2924	Manufacture of other general-purpose machines n.e.c.	99	36	13	4	26	20
2956	Manufacture of other special-purpose machinery n.e.c.	94	29	16	4	33	18
3162	Manufacture of other electrical equipment n.e.c.	25	36	24	4	28	8
3622	Manufacture of jewellery and related articles n.e.c.	8	25	13	0	<b>50</b>	13
3663	Other manufacturing n.e.c.	9	11	<b>67</b>	0	11	11
4521	General construction of buildings and civil engineering works	100	6	42	27	19	6
5100	Wholesale trade and commission trade (except of motor vehicles/cycles)	22	0	27	27	32	14
5147	Wholesale trade with other household goods	18	6	11	11	28	44
5187	Wholesale trade with other machines and equipment for industry and trade	40	8	13	3	30	47
5190	Other wholesale trade	24	17	4	17	38	25
5212	Other retail sales in non-specialised stores	12	0	17	33	8	42
5248	Other retail sale in specialized stores	26	8	23	12	31	27
6340	Activities of other transport agencies	18	0	17	27	33	22
7487	Business services n.e.c.	16	13	13	<b>50</b>	6	6

<sup>a</sup> Dominant clusters (50% or more firms belong to *one* cluster) are in bold

## Data availability

The data used in this paper stem from the “Swiss Innovation Survey” conducted by the KOF Swiss Economic Institute of the ETH Zurich every third year since 1990. We draw on the data of four waves of the survey covering the period 1999-2008. In these years, the questionnaire did practically not change, at least with respect to the questions of interest.

The survey is based on a random sample of companies (five or more employees) drawn from the official enterprise census. It covers the entire business sector stratified by 29 industries and 3 industry-specific firm size classes (with full coverage of large firms). The response rate varied among the four waves of the survey in the range of 36% to 40%. For each wave, we conducted a unit non-response analysis based on a few innovation-related variables, which, however, did not show any sign of a serious selectivity bias with respect to the sample.

The sample (unbalanced panel) used in this study is confined to innovative companies (firms that realised product and/or process innovations in the year of the survey or the two preceding years). It contains 5645 observations out of a total of 9'393 companies that provided the required information; the share of innovative firms is thus about 60%. The distribution of the observations across the four waves of the surveys is quite even.

The Tables 1 and 4 show the definition and measurement of the variables we use for the identification, description and evaluation of the innovation modes (cluster analysis). In Table 9, we define the variables serving to estimate econometrically the relationship between cluster affiliation and firm performance. Based on these tables, it is easy to identify the correspondence between the variables we use in the analysis and the underlying questions contained in questionnaires. The reader may download the questionnaire applied in the four waves of the survey from [www.kof.ethz.ch/en/surveys/structural-surveys/kof-innovation-survey.html](http://www.kof.ethz.ch/en/surveys/structural-surveys/kof-innovation-survey.html)).

The firm-level data are highly confidential (as we promised the firms participating in the survey). However, we can provide the data upon request, though only under the following conditions:

1. The user of the data must be a PhD student or a staff member of a research institution.
2. The user has to provide a short description of the planned research.
3. The analysis of the data has to take place at the author's workplace, i.e. at the KOF Swiss Economic Institute, Zurich.

Applications for the use of data should be addressed to:

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