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Innovation strategies of Swiss firms: identification, dynamics and intra-industry heterogeneity

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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 change of the economy. Thirdly, he examines, based on a large number of 4-digit industries, 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 more important as a 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 its 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 and Porter 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 industries 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 is based on one 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 mode of innovation, 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 measuring 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 highly disaggregated level (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 *impact of a firm's innovation strategy and its industry affiliation on economic performance*. The strategic management view would be superior if the effect on firm performance due to the choice of specific innovation strategies is larger than that attributed to industry affiliation, having controlled for other factors determining a firm's success. The opposite result (i.e., if industry affiliation is more important as a factor determining performance) would support the technological regime approach. 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 few studies dealing with this topic applying econometric methods (Hollenstein 2003; Frenz and Lambert 2009, 2012; Sanchez 2014). Moreover, since the theoretical basis of these analyses – with the exception of Hollenstein (2003) – is not convincing, as they neglect the productivity effect of the classical production inputs (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 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. Subsequently, we analyse the intra-industry heterogeneity of innovation strategies at the 4-digit industry level. In Section 6, we present the econometric estimates of the productivity model, which contains – apart from the production inputs and firm/industry level heterogeneities – a firm's innovation strategies and its industry affiliation. 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 big 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).[1] 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 several indicators of innovation we include in this paper are not (only) technology-related (or do not exclude non-technological innovations). As examples, we may mention measures like "the significance of innovations in economic terms", "the outlays for training related to innovation and IT", "the expenditures for the introduction of innovative products on the market", or "the 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).[2]

The dataset constitutes an *unbalanced panel* of four cross-sections as not all firms included in the 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 final sample are quite

[1] The questionnaires used in the four waves of the survey is available in a German, French and Italian version on www.kof.ethz.ch/en/surveys/structural-surveys/kof-innovation-survey.html.

[2] Only more recent waves of the Swiss 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.

evenly distributed over the four cross-sections (24%, 27%, 26% and 23%), reflecting the fact that the response rate and the share of innovative firms do not much diverge among the four waves of the survey.

We correct the data for *item* non-response by *imputing missing values* ("multiple imputation"; see Rubin 1987) to avoid a bias in the final dataset and to prevent a significant reduction of the size of the sample. Renouncing to use imputed values would endanger (if not make impossible) an analysis of the core topics of this paper, as we would have to drop a firm from the dataset as soon as the *value for one single variable is missing*. As we need about forty variables to identify and evaluate the innovation modes (see Section 3), the results of this basic step of the analysis would become much less reliable. Obviously, the same is true for Section 4 (switches of innovation strategies over time) and Section 6 (relationship between innovation strategies and firm performance). Moreover, without including imputed values, a differentiated analysis of the intra-industry heterogeneity of innovation strategies would be impossible, as it requires a large number of 4-digit industries, each containing a certain minimum number of firms (Section 5). To illustrate the *effect of not using imputed values*, we shall compare the results of the factor analysis based on data including and excluding imputed values (see Subsection 3.2).

Table A.1 in the Appendix shows the composition of the final sample by sector and industry. It turns out that it is largely representative for the basic sample used in the four surveys.

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 largely use 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*. We capture (a) the *generation* of innovations by using eight *input-side indicators* (e.g., expenditures for research, expenditures for IT hardware and software, etc.). Furthermore, we take into account (b) the (intermediate) results of innovative activity based on five *output-side indicators* (e.g., patents, technical significance of process innovations, etc.). Finally, we consider (c) the *implementation* of the novelties, i.e. the introduction of product innovations on the market and of process innovations within the firm. Hence, there is a *coherent logic guiding the selection* of the three types of indicators. Besides, we may point to the fact that two out of the fifteen indicators explicitly are related to IT. The same is hardly ever the case in previous research, which obviously is a deficiency in view of the technological trends of the last three decades. For a list of the fifteen indicators used in our analysis as well as the precise definition and measurement of these variables, see Table 1.

We do not conduct the cluster analysis *directly* with these variables. Instead, we start by standardising and synthesising the information contained in the fifteen individual measures into a small number of variables by means of a *principal component factor analysis* (SAS procedure FACTOR, method=principal). The resulting *factors* are uncorrelated standardised variables capturing the common information of the fifteen original variables. Subsequently, we perform a *non-hierarchical cluster analysis* of these factors using the SAS procedure FASTCLUS, which is an efficient procedure for clustering large data sets. The method allocates the firms to 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). The procedure of "nearest centroid sorting" 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

Table 1: Innovation indicators used in the factor analysis

Innovation indicator	Measurement scale and value range	
Input-oriented measures		
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 and IT	Ordinal	1, …, 5
- Expenditures for the introduction of innovative products on the market	Ordinal	1, …, 5
Output-oriented measures		
Patent applications (yes/no)	Nominal	1, 0
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
Market-oriented measures		
Sales share of new or significantly improved products (%)	Metric	0, …, 100
Cost reduction due to process innovations (yes/no)	Nominal	1, 0

another group, if it proves to be closer to that group's centre than to the centre of the initial group. This iterative process, during which close groups are merged and distant ones split, continues until stability is achieved with a *predetermined number of clusters* (see Manly 1986).[3]

In the *second step of our methodological approach*, which distinguishes our procedure from that used in previous studies, we examine whether we effectively may interpret the clusters identified in the first step as different "modes of innovation". We follow the reasoning of the statistical literature according to which one cannot assess the quality of the results of a cluster analysis only by means of statistical criteria. Rather it is indispensable to provide an "external validation" of the clusters based on a *contextual (theoretical) assessment* (see, e.g., Kaufmann and Pape 1996). To this end, we characterise the clusters in terms of *three categories of variables*: Firstly, the innovation indicators used in the clustering process, complemented by several measures capturing the direction of innovation efforts in more detail ("objectives of innovation"). Secondly, a series of important determinants of innovation activity, as postulated in the "economics of innovation" (see, e.g., the surveys of Cohen 1995, 2010). These pertain to the demand side (market prospects, intensity of competition, market structure) and the supply side (technological/innovation opportunities, appropriability of knowledge, human resources) of the innovation process. Thirdly, a set of variables characterising a firm's knowledge network (intensity of use of several external sources of knowledge as well as the relevance of R&D contracts and of institutionalised R&D co-operations). According to the model of Arvanitis and Hollenstein (1994), we also may interpret the indicators of a firm's knowledge network as supply side determinants of innovation activity.

Most researchers seeking to identify innovation modes (see the references we mention below in subsection 3.4) use at the clustering stage not only variables of the first category, i.e. innovation indicators, as we do, but also include variables of the third category (external knowledge network), whereas they largely neglect measures of the second category (i.e., the determinants of innovation activities). In so doing, previous studies end up with hardly any variables they can use as "external criteria" (i.e., variables *not* included in the clustering process) for evaluating the plausibility of the innovation modes from an independent, theory-based point of view.

3.2 Results of the factor and the cluster analysis

The results of the *preliminary step* for identifying innovation modes, i.e. the *factor analysis* of the fifteen innovation indicators listed in Table 1 are satisfactory (see Table 2). The five factors we extract account for 60.5% of the total variance. The first factor, capturing 22.6% of the total variance, reflects the technological and economic significance of process innovations and innovation-related cost reductions. The second factor, accounting for 13.3% of the variance, represents the science-related innovation input (expenditures for research and for development, respectively) and the science-oriented innovation output (patent applications). The third factor (10.2% of total variance) refers to the technical and economic significance of product inno-

[3] We calculate solutions with different numbers of clusters among which we pick the one that is most suitable according to the criteria mentioned further down in this subsection.

vations and to the sales of new or significantly improved products. The fourth factor (8.0% of total variance) focuses on the total of innovation-related follow-up investments as well as on specific components of these expenses (outlays for machinery and equipment, expenditures for the introduction of new products on the market). At the core of the fifth factor (6.4% of total variance) 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*, with each representing a *specific orientation of innovation activity*: "process-orientation" (F1), "science-orientation" (F2), "product-orientation" (F3), "investment-orientation" (F4), and "IT-orientation" (F5).

The statistical properties of this five-factor solution are not fully in line with the methodological recommendations of OECD (2008, p.89), as the contribution of the factors 4 and 5 in explaining the total variance is not sufficiently large (i.e., less than 10%). However, solutions with a lower or a higher number of factors perform worse in terms of the OECD criteria. Moreover, we remind that the literature emphasises that one should not mechanically apply purely statistical criteria. Rather the factor pattern has to allow a sensible interpretation of the results given the problem at hand (Kaufmann and Pape 1996). In this respect, the five-factor solution is clearly superior to any alternative. Versions with three or four factors put together in one single factor various aspects of innovation activity whose meaning diverges too much from each other, whereas in the case of six (or more) factors some closely related dimensions of the innovation behaviour are assigned to different factors. Furthermore, and very important, a solution with five factors yields the most convincing results in the subsequent cluster analysis both in statistical terms and with respect to the interpretation of the clusters. Against this background, we stick to a five-factor solution.[4]

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. To determine the *optimal number of clusters*, we take into account three criteria, that is: (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

[4] As mentioned in Section 2, the number of observations we could use for applying the two-step methodology would be much smaller if we did not impute missing values. Consequently, an analysis of the more complex problems we tackle in the Sections 4 to 6 would not be feasible. Nevertheless, to *illustrate the effect of using or not using imputed data* we take as an *example* the results of the *factor analysis*. Firstly, on purely statistical grounds, the optimal solution is one with five factors, independent on whether we impute missing values or whether we renounce to do so, although, in both cases,, one of the three OECD criteria is not fulfilled, i.e., the variance explained by the fourth and the fifth factor is below 10%. However, the use of imputed values yields slightly better results. Secondly, the problem-oriented interpretation of the five factors is more convincing based on the dataset that includes imputed values. Nevertheless, the difference between the two approaches is not too large, as the interpretation of three of the five factors is very similar. Thirdly, the *subsequent cluster analysis* is clearly superior if we include the observations with imputed values. This version provides a set of innovation modes (five clusters) that corresponds to a higher extent to the insights provided by the "economics of innovation" than an analysis based on a dataset without imputations.

Table 2: Factor analysis of the innovation indicators[a]

Innovation indicator	Rotated factor pattern (varimax) [b]				
	F1	F2	F3	F4	F5
Significance of process innovations in economic terms	**0.88**	-0.01	0.11	0.03	0.13
Significance of process innovations in technical terms	**0.86**	-0.03	0.04	0.03	0.16
Cost-reduction due to process innovations	**0.60**	0.13	-0.04	0.17	-0.10
Expenditures for research	0.06	**0.80**	0.07	0.02	0.11
Expenditures for development	0.02	**0.78**	0.20	0.17	0.09
Patent applications	0.03	**0.63**	0.12	0.15	-0.16
Significance of product innovations in economic terms	0.03	0.09	**0.86**	0.13	-0.02
Significance of product innovations in technical terms	0.04	0.11	**0.84**	0.11	0.00
Sales share of new or significantly improved products	0.04	0.30	**0.45**	-0.10	0.12
Innovation-related follow-up expenditures for machinery and equipment	0.18	0.10	0.05	**0.80**	-0.01
Innovation-related follow-up expenditures in general	0.09	0.13	0.03	**0.73**	0.24
Expenditures for the introduction of innovative products on the market	-0.11	0.30	0.32	**0.44**	0.28
Acquisition of external knowledge (consultancy, licences, etc.)	-0.01	0.17	-0.00	0.09	**0.72**
Expenditures for IT (hardware and software)	0.15	-0.12	0.01	0.05	**0.71**
Follow-up expenditures for training activities related to innovation and IT	0.04	0.00	0.12	0.**46**	**0.59**
Number of observations					5645
Kaiser’s overall measure of sampling adequacy (MSA)					0.71
Eigenvalue of the each individual factor	3.39	1.99	1.53	1.20	0.96
Final communality estimate (total)					9.07
Variance accounted for by each factor (%)	22.6	13.3	10.2	8.00	6.40
Variance accounted for by the sum of the five factors (%)					60.5
Root mean square off-diagonal residuals (RMSE)					0.078

[a] For variable definitions, see Table 1. [b] Factor values greater than 0.40 are in bold to facilitate the interpretation of the factor pattern.

guarantee a reliable mapping of firms and clusters, should exceed a certain minimum level, and (c) a *preliminary* overall assessment of the plausibility of the clusters ("do the five clusters represent 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, hence violating criterion (c).

We thus arrive at a solution with *five clusters* (see Table 3). It is satisfactory in statistical terms, as 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 strategies. The clusters 1 and 2 focus unambiguously on *one* specific factor, i.e. F2 (science-orientation) and F4 (investment-orientation), respectively. 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 characteristics of 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 product-oriented.

In sum, the cluster analysis yields five categories of firms, which we *preliminarily* may interpret as specific modes of innovation. We *definitely* assess the adequacy of the five innovation modes 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.

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, 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 characteristics of the firms.

Table 3: Cluster analysis [a]

Factors	Cluster 1 *Science-based strategy* (N = 1021)	Cluster 2 *Investment-based strategy* (N = 1397)	Cluster 3 *IT/process-oriented strategy* (N = 802)	Cluster 4 *Process/product-oriented strategy* (N = 1555)	Cluster 5 *IT/product-oriented strategy* (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
Statistics					
Number of observations	5645				
Pseudo-F	779***				
Expected overall R^2	0.44				

[a] The cluster analysis relies on the results of the factor analysis that identified five factors (F1 to F5); see Table 2.

Among the *determinants* of innovation (see, e.g., Cohen 2010), we take into account, on the *demand side*, the medium-term prospects for a firm's markets, the intensity of price competition and of non-price competition in the product market, and the market structure (number of principal competitors of the company 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 reflecting the availability of human resources. We take account of human capital, firstly, as firms that are 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, a number of variables representing the intensity of use of external knowledge sources in an informal way (customers, several types of suppliers, competitors, consultancy firms, universities, other scientific institutions, generally accessible sources such as patent disclosures, 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 a few structural characteristics of the firms (size, age, export orientation) to get some insight into the composition of the five clusters. For the precise definition and the measurement of the variables used to evaluate the adequacy of the modes of innovation, see Table 4.

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 five clusters* in terms of these five categories of variables. This allows to assessing whether they *effectively* represent specific modes of innovation (innovation strategies). For *more details* on the pattern of the underlying variables by cluster, we have to ask the reader to study the detailed *Tables A.2a to A.2e* in the *appendix*.

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-

Table 4: Indicators used to characterise and evaluate the clusters

Indicator	Measurement scale and value range	
Innovative activity		
- Innovation indicators used in the factor analysis (see Table 1)		
Objectives of innovation		
- Relevance of several product-related objectives	Ordinal	1, …, 5
- Relevance of several process-related objectives	Ordinal	1, …, 5
Determinants of innovation		
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 five principal competitors at world level (yes/no)	Nominal	1, 0
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
Knowledge network		
Sources of knowledge		
- Intensity of use of 14 types of external knowledge sources	Ordinal	1, …, 5
R&D contracts		
- Domestic contractor (yes/no)	Nominal	1, 0
- Foreign contractor (yes/no)	Nominal	1, 0
R&D co-operation		
- Domestic partner (yes/no)	Nominal	1, 0
- Foreign partner (yes/no)	Nominal	1, 0
Structural characteristics of the firm		
Firm size		
- Number of employees (mean, median)	Metric	5 or more
- Share of firms (%) by six size classes (no. of employees): 5-19, 20-49, 50-99, 100-249, 250-499, 500 or more	Metric	0, …, 100
Firm age		
- Less than ten years old (yes/no)	Nominal	1, 0
Export intensity		
- Share of firms by export to sales ratio (%): 0-1, 2-20, 21-60, 61-100 (%):	Metric	0, , 100

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% of the firms of this cluster): chemicals/pharmaceuticals, non-electrical machinery, electrical machinery and electronics/scientific instruments. This 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 (strong price competition, average demand prospects), 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 substantial share of large companies and a very high proportion of firms that are active solely in domestic markets. Firm age is about equal to the overall mean. The companies 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 and innovation 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 as well as 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 large 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 (computer networks, fairs, professional journals) at the core. Companies of this cluster primarily serve 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 the number of principal competitors on the world market (market structure). 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), the other IT/product-oriented (cluster 5). Another two modes contain 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 investigations based on a cluster analysis* 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 a maximum 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) formal and informal external knowledge sources, and (g) appropriability of knowledge. 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 category of measures.

Against this background, it is not sensible to aim for a one-two-one comparison of the results of previous work with our five-cluster classification. Such an endeavour is hardly feasible, as the available studies substantially differ from each other in terms of the type and number of indicators included. In addition, a *comparison is not a priority* of our analysis. The identification of innovation modes rather is a *preliminary but indispensable step for tackling the core topics of our research*, i.e., (a) the dynamics of innovation strategies (Section 4), (b) the intra-industry heterogeneity of innovation modes (Section 5), and (c) the relationship between the choice of a specific innovation strategy and firm performance (Section 6).

Nevertheless, we may draw *three basic conclusions from a comparison with previous research.* Firstly, several of the available studies identify, at least in essence, two of our five innovation clusters, i.e. the "high-profile science-based strategy" (cluster 1) and the "low-profile investment-based strategy" (cluster 2). In some instances, we also find a *tendency* for identifying a cluster that is not too much different from our cluster 4 ("low-profile process/product-oriented innovators"). Secondly, our analysis is the only one that identifies two clusters for which an intensive use of IT is constituent, the one process-oriented (cluster 3), and the other product-oriented (cluster 5).[5] The absence of any IT-oriented cluster in other analyses

[5] There is a *certain* similarity between our cluster 3 ("IT-based process-oriented strategy") and one of the innovation modes identified by Frenz and Lambert (2012) and Srholec and Verspagen (2012) based on CIS data. These

is quite surprising, given the high importance of this technology since the 1990s. This feature of previous studies is a substantial deficiency, which primarily is the consequence of the fact that other researchers mostly rely on data stemming from the "Community Innovation Survey" (CIS) that does not provide any IT-related information. Thirdly, we remind that these studies did not evaluate the adequacy of the identified innovation clusters from an independent theory-based point of view, i.e., using for this purpose a set of variables that, according to the "economics of innovation", determine a firm's innovation activity. To our knowledge, Hollenstein (2003) is the only exception.

The comparison with previous work takes into account only studies that are based on a *cluster analysis* of a number of innovation indicators ("*bottom-up approach*"). We *do not include research* relying on a "*top-down approach*" that rests on an *ex ante-definition of innovation modes using some a priori classification rules*. In this vein, Roud (2018) combines two (simple) selection criteria to determine five innovation modes, i.e., (a) national vs. international market-orientation of a company, and (b) new-to-market vs. new-to-firm innovations. Peneder (2010) refers to four basic dimensions of the "technological regime approach" (creative vs. adaptive innovation behaviour, technological opportunities, appropriability conditions and cumulativeness of knowledge). He uses these elements to characterise the innovation behaviour of firms at the 2-digit industry level, with each industry exhibiting a specific combination of the four dimension.[6] The latter paper has a clear theoretical foundation, but its perspective is definitely opposed to our "bottom-up approach" reflecting the "strategic management concept". As we do not impose a priori some selection rules, we are able to assess whether the innovation modes identified in a first step (cluster analysis) are consistent with the basic insights of the "economics of innovation" (see above). Besides, we are in a position to assess the relative merits of the "technological regime approach" and the "strategic management concept" of the firms' innovation behaviour (see the Sections 5 and 6).

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.

researchers find a category of firms for which "process-related organisational innovations" are at the core, but they do not provide any information on the use of IT.

[6] Preserving his top-down approach, Peneder (2010) also analyses the intra-industry variance of the four constituent dimensions of the technological regime approach (see Section 5).

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.[7] 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 data are 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.[8]

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 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 alternative strategies is 25%, presuming 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

[7] 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.

[8] 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.

innovation-related environment changes quite rapidly and/or 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 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 or 2002 to 2008) 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 the 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. *two 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.

Table 5: Movements of firms between clusters over a three-year period[a]

	Number of firms moving between the clusters *Columns: inflows* from other clusters *Rows: outflows* to other clusters					
Innovation strategy (Cluster 1 to 5)	Science-based	Invest-ment-based	IT/ process-oriented	Process/ product-oriented	IT/ product-oriented	Total
CL1: Science-based	///	55	22	48	46	171
CL2: Investment-based	67	///	49	79	51	246
CL3: IT/process-oriented	22	34	///	56	31	143
CL4: Process/product-oriented	66	117	51	///	69	303
CL5: IT/product-oriented	36	47	34	69	///	186
Total	191	253	156	252	197	1049

[a] The slashes on the diagonal indicate that, at this stage of the analysis, we do not consider the companies sticking to their current strategy for reasons mentioned in the text.

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 Table 6 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 strategies (nearly 50% vs. 25%). The interpretation of the results would be more complicated, if we would include from the very beginning the firms sticking to their initial strategy. We shall take account of this information later on.

In the following, we do not comment on Table 5, which shows the *absolute number of transitions* from one to another cluster (CL1 to CL5). This table only serves to calculate the ratio of the number of firms attracted by a specific cluster from other ones (inflows) to the number of firms moving away from the current cluster to other ones (outflows). We show in Table 6 the *ratios of inflows to outflows* of firms for each strategy. These ratios allow to assessing at a glance the *relative attractiveness of the five strategies*.

To provide an example of how to read Table 6, 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 (row 5 of column 1). 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, Table 6 shows that *cluster 5 (IT/product-oriented strategy)* is on the winning side as well, although the total net inflow is 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 sum up, Table 6 shows that cluster 1 (science-based strategy) and, less pronounced, the clusters 3 and 5 (IT/process-oriented 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

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

	Ratio of *inflows* from and *outflows* to other clusters (*columns*)				
Innovation strategy (Cluster 1 to 5)	Science-based	Investment-based	IT/ process-oriented	Process/ product-oriented	IT/ product-oriented
CL1: Science-based	///	0.82	1.00	0.73	1.28
CL2: Investment-based	1.22	///	1.44	0.68	1.09
CL3: IT/process-oriented	1.00	0.69	///	1.10	0.91
CL4: Process/product-oriented	1.38	1.48	0.91	///	1.00
CL5: IT/product-oriented	0.78	0.92	1.10	1.00	///
Total	1.12	1.03	1.09	0.83	1.06

[a] The slashes on the diagonal indicate that, at this stage of the analysis, we do not consider the companies sticking to their current strategy for reasons mentioned in the text.

(investment-based strategy), the total of inflows from the other clusters is quite similar to the total of outflows.

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 the 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 other innovation modes (net winner), and (b) the share of firms sticking to the current strategy is particularly large.

4.4 Assessment of the results

The overall frequency of the switches from one to another strategy of innovation is high, even within a short 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 into their innovation strategy a disruptive type of technology like IT within a short period. 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 many firms belonging to this quite large segment of the Swiss economy – it covers about a quarter of the sample – might be indispensable. The concordance of the dynamics of innovation strategies and the direction of the structural change required in the highly advanced economy of Switzerland underlines 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 tends to be 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), or the business sector as a whole (e.g., Castellacci 2008).

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"). In addition, it follows that a specific innovation strategy may be present in different industries. 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 several 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 partly 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). These analyses throughout find a substantial intra-industry variation of innovation modes, which seems to be consistent with the strategic management view (heterogeneity hypothesis). At the same time, 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. However, it is generally questionable, whether the observed *heterogeneity within 2-digit industries* allows to rejecting the homogeneity hypothesis, as industries at this level of aggregation mostly cover very different lines of production (Archibugi 2001).[9] Therefore, it is indispensable to analyse the intra-industry variance of innovation strategies at a more disaggregated level.

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.[10] The results of this detailed analysis referring to the Finnish economy[11] 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 production activities than industries at a higher level of aggregation. However, as the study of Leiponen and Drejer (2007) rests on a 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.[12] In so doing, we may expect a more reliable assessment of the heterogeneity hypothesis.

In advance of presenting the results of this 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 NACE classification, and (b) for five sectors representing groups of 2-digit industries: high-tech manufacturing, low-tech manufacturing,

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[9] This concern does not only apply to studies based on a cluster analysis ("bottom-up approach) but also pertains to the "top-down approach", which is used, for example, by Peneder (2010). At the 2-digit industry level, he found a substantial intra-industry variance of the four core elements of the "technological regime approach".

[10] 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.

[11] 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.

[12] 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.

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
Low-tech manufacturing	16.3	35.8	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
High-tech manufacturing	33.6	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
Construction	6.1	34.6	20.3	27.1	11.9	100
Knowledge-intensive services	9.2	9.1	33.5	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
Other services	6.1	22.1	19.8	29.0	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
Total	18.3	25.0	14.3	27.1	15.3	100

construction, knowledge-intensive services and "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 or two innovation modes, whereas for other industries, we find a rather wide distribution over the five clusters.

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 the 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 is less knowledge-intensive, no innovation strategy generally stands out. Nevertheless, three of these industries have a certain 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.

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 industry (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 production activities should be more homogeneous than they are in 2-digit industries. To this end, we replicate for Switzerland the study of Leiponen and Drejer (2007) based on a substantially larger database. By choosing the same approach, 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.[13] These alternatives 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, probably more adequate, "at least ten" companies. Our large dataset allows to analysing the intra-industry distribution of firms by cluster for *153 industries* based on a cut-off point of eight firms, and for *126 industries* 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. Finally, we also calculate (Switzerland only), the distribution over the five clusters based on a higher threshold of the number of companies (industries with *at least fifteen* companies). In so doing, we end-up with *103 industries*.

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 (4-digit). In *column 2 of*

[13] 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 innovation modes. For the problems encountered in comparing innovation clusters between different studies, see subsection 3.4.

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).

The *upper part of Table 8* (row 1.A to 2.C) shows the share of 4-digit 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 industries 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 industries without a dominant 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 Swiss and the Danish economy – perhaps 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 results do not diverge to a higher extent. Finally, we illustrate the intra-industry heterogeneity using a higher cut-off point, i.e. *"at least fifteen companies"* (results for Switzerland only). In this case, the number of 4-digit industries, as shown in row 1.C, decreases to 103 as against 126 in case of a threshold of *"at least ten firms"* (row 1.B). We find that the percentage of 4-digit industries without a dominant cluster is only slightly higher than in the case of a threshold of ten companies; see row 1.C (82%) vs. 1.B (78%). Hence, we again conclude that the degree of intra-industry heterogeneity with respect to the five clusters is large.

To check the *robustness of the 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, industries 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, industries 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"), 105 industries (with "at least *ten* firms") and 83 industries (with "at least *fifteen* firms"). It turns out that this reduction of the number of industries hardly changes the results (see Table 8: row 2.A vs. 1.A, row 2.B vs. 1.B and row 2.C vs. 1.C).

Another source of distortion of the results could be due to the inclusion of (very) big companies, as these 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 present 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 *distribution of industries over the five clusters*. According to the results shown in 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

Table 8: Relationship between innovation modes (clusters) and industry affiliation (*4-digit NACE classification*)[a]

	Switzerland [b] (1)	Finland [c] (2)
1.A: Share of industries (*at least 8 firms*) *without* a dominating cluster (Switzerland 153 industries; Finland: 21 industries)	71%	61%
1.B: Share of industries (*at least 10 firms*) *without* a dominating cluster (Switzerland: 126 industries; Finland: 14 industries)	78%	80%
1.C: Share of industries (*at least 15 firms*) *without* a dominating cluster (Switzerland only: 103 industries)	82%	-
2.A: Share of industries (*at least 8 firms*) with *clearly specified activities without* a dominating cluster (Switzerland only: 128 industries)	69%	-
2.B: Share of industries (*at least 10 firms*) with *clearly specified activities without* a dominating cluster (Switzerland only: 105 industries)	75%	-
2.C: Share of industries (*at least 15 firms*) with *clearly specified activities without* a dominating cluster (Switzerland only: 83 industries)	80%	-
Industries (*at least 8 firms*): (Switzerland: 153 industries; Finland: 21 industries)		
3.A: Share of industries appearing in *all 5 clusters*	59%	-
3.B: Share of industries appearing in *at least 4 out of the 5 clusters*	88%	63%
4. *Number of clusters* with firms from at least 75% of the industries	5 (out of 5)	3 (out of 5)

[a] A cluster is defined as dominating if 50% or more firms are in *one* cluster. [b]The figures for *Switzerland* are calculated from *Table A.3* in the Appendix. The values in row 1.A, 1.B, 1.C as well as 3.A, 3.B and 4 are based on *part A and B* of that table. In contrast, we used only data from part A of Table A.3 for calculating the values shown in row 2.A, 2.B and 2.C. [c]The *data* for *Finland* stem from Table 6 of Leiponen and Drejer (2007) and from calculations based on Table A1 in Appendix A of that study.

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.[14] The results based on the two additional types of indicators confirm the findings presented in the upper part of Table 8. Altogether, we conclude that, independent of the indicator used, the intra-industry heterogeneity of the firms' innovation strategies is large in both countries, and even higher in Switzerland than in Finland.

One may object that the threshold used so far to distinguish *dominant* from *non-dominant* clusters is too high (we remind that a cluster is defined as dominant, if *at least 50%* of the firms of an industry belong to *one specific cluster*). 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 *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% in the case of a cut-off point of "at least ten firms.[15] The difference, however, is much smaller if we only consider the 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 not much decreases if we use a threshold of 40% instead of 50%. We get a reduction from 69% to 63% for industries containing "at least eight firms" and from 75% to 68% in the case of industries with "at least ten firms". We conclude that the robustness checks reported on in this paragraph are *largely* in line with the heterogeneity hypothesis although the share of industries with no dominant cluster substantially decreases if we use the criterion of 40% instead of 50%.

We remind that quite many *2-digit industries* exhibit a certain concentration of firms on one or two specific clusters (see Table 7 above). Hence, the results at the 2-digit and the 4-digit level seem to contradict each other to a certain extent. However, this is not necessarily the case, since the intra-industry distribution of the firms over the five clusters could be similar for the 4-digit and the 2-digit industries to which they belong. We investigate this aspect 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 stronger 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

[14] The choice of the 75% criterion is arbitrary, but we stick to it, because otherwise we cannot compare the results with those for Finland.

[15] Table A1 in Appendix A of Leiponen and Drejer (2007) allows to calculating also for Finland the share of industries without a dominating cluster based on the lower *threshold of 40%* for the cut-off points of "at least eight firms" and "at least ten firms" per industry, respectively. We find that in both cases the share of industries without a dominating cluster decreases by the same order of magnitude as in the Swiss economy.

not very large; nevertheless, 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) that are largely homogenous in terms of their production activities. At the same time, it turns out that the distribution of firms over the five innovation clusters for a substantial proportion of 4-digit industries is similar to that of the corresponding 2-digit industries and shows a certain concentration on one or two clusters.

This pattern of results indicates that a firm has a substantial room of manoeuvre for making strategic choices with respect to its innovation behaviour within narrowly defined activities (4-digit). However, some structural factors common to many companies of a more aggregated industry (2-digit) seem to reduce the number and type of feasible strategies. Such restrictions primarily may 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 quite similar for the firms belonging to the same industry.

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, we conclude that the *strategic management* of innovation 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 findings add to the evidence provided in the previous section where we primarily dealt with the intra-industry heterogeneity of innovation modes.

In the empirical analysis, we use *labour productivity* as a proxy of firm performance (nominal value added per employee; full-time equivalents), which is the *dependent variable* of our econometric model. The first row of Table 9 shows the average labour productivity 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 model estimation, we use pooled data stemming from the four waves of the Swiss Innovation Survey conducted in the period 1999 to 2008.[16]

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, as some researcher do, does not allow to assessing whether there is a significant association between the choice of a specific innovation mode and labour productivity, because other factors also exert an influence on labour productivity, or do so even to a higher extent.[17] For example, it is not surprising that firms that intensively use physical capital (high capital to labour ratio) achieve, on average, a higher labour productivity than companies whose production is less capital intensive (see cluster 3 vs. cluster 2 and 4, respectively).

Against this background, we specify a model that explains a firm's labour productivity using *four categories of variables*. The *first* one represents the five *innovation strategies*. To specify these variables, we apply the procedure used by Frenz and Lambert (2012) and Sanchez (2014). Accordingly, we capture the innovation strategies by inserting for each of them the firms' factor scores we used as inputs for the cluster analysis that served to identify the modes of innovation. 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, which reflects the particular capabilities of a firm, yields a productivity premium.

The *second* group of variables includes the classical *input factors of a production function*, i.e. the intensity of use of physical capital, human capital and R&D capital. The coefficients of these variables obviously should be positive. From a theoretical point of view, the production factors are the most important variables for explaining productivity.

Thirdly, we control for a set of variables representing *firm and industry heterogeneities*. More specifically, we take into account six variables, i.e., firm size, foreign ownership of the company, firm age, technological and innovation potential, export opportunities, and intensity of competition. The productivity of *large firms* should be particularly high, as they can exploit economies of scale and scope and profit from market power. *Foreign firms* have to be more productive than domestic ones to compensate for higher transaction costs. Furthermore, we posit that *young companies*, as we control for firm size, should be more productive than an old ones, because they often are more dynamic and flexible. Furthermore, according to Acemoglu et al. (2018), a firm's "*innovation capacity*", which we approximate by the variable "techno-

[16] 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.

[17] 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 as well as some variables that would be appropriate to identify, at firm level, an association between cluster affiliation and firm performance.

Table 9: Means of the 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
Dependent variable						
Labour productivity *(nominal value added per employee, 1000 CHF)*	176	157	187	161	172	168
Independent variables						
Cluster affiliation						
- Share of firms by innovation strategy (% yes)	18	25	14	28	15	100
Factor input						
- Capital to labour ratio (capital income per employee, 1000 CHF)	86	74	95	77	83	81
- 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
Structural firm and industry characteristics						
- Firm size (number of employees, full-time equivalents)	440	389	456	293	213	355
- The firm is foreign-owned firm (% yes)	22	14	10	16	19	16
- The firm is less than ten years old (% yes)	7	6	7	7	8	7
- Technological/innovation potential in/around the firm's fields of activity[a]	43	26	29	28	36	32
- The firm is an exporter of goods/services (% yes)	87	65	44	62	55	63
- The firm has more than five but less than ten principal competitors (% yes)	36	27	27	27	28	29

[a] Percentage share of firms with score 4 or 5 (high potential) on a five-point ordinal scale.

logical/innovation potential in/around a firm's fields of activity", also should positively correlate with productivity. Besides, we presume that large *"export opportunities"* are another driver of innovation and productivity (Aghion et al. 2018). Finally, in analogy to Aghion et al. (2005), which found an inverted U-shaped relationship between competition and innovativeness, we hypothesise that an *"intermediate degree of competition"* is the most favourable market environment for increasing productivity.

Fourthly, we insert 28 two-digit *industry dummies* to capture productivity effects that are common to all firms affiliated to a specific industry. The technological regime approach would imply that the coefficients of the industry dummies are (jointly) significant. As the industry dummies also capture the influence on productivity exerted by variables not explicitly specified in the model, we cannot exclude an *"omitted variable bias"*. However, we presume that such a (potential) bias, which would reduce the "true" effect of industry affiliation, is not substantial in view of the detailed specification of our model.

Finally, it is necessary to point to *two econometric problems*. The first one arises 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 response rates, varying macroeconomic conditions, etc.), the explanatory variables could be *endogenous*. Consequently, 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 still use expressions like "impact on productivity" or "productivity effect", but always being aware of the fact that *we cannot establish causal links*. We may note that previous studies suffer from the same deficiency, as they use data stemming from one single cross-section.[18] *Multicollinearity* is another problem we have to take into account. A few explanatory variables positively correlate with some of the innovation modes, particularly (but not only) with the science-based strategy. To mention are, in the first place, the variables "R&D intensity", "innovation capacity" (technological/innovation potential) and some of the industry dummies that reflect high tech activities. To some extent, we shall deal with this problem in estimating the productivity model.

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; logarithm). The columns 1 to 4 show some "initial stages" of model estimation. The equations displayed in the columns 1 to 3 highlight the productivity effect of the variables representing the firms' choice of specific innovation

[18] As we use pooled data of an unbalanced panel as a basis for identifying the five innovation modes, we are not able to account for time lags in estimating the relationship between innovation strategies and productivity. The same holds for other independent variables.

Table 10: Relationship between innovation strategies and labour productivity *(nominal value added per employee, log)* [a]
(OLS estimation; pooled data 1999, 2002, 2005 and 2008)

Dependent variable: *labour productivity*	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Clusters [b]								
Science-based strategy	.028***	//	.031***	.004	.000	-.001	.024***	.000
	(.01)		(.01)	(.00)	(.00)	(.00)	(.01)	(.00)
Investment-based strategy	.021***	//	.021***	.005*	.002	.001	.015***	.002
	(.01)		(.01)	(.00)	(.00)	(.00)	(.01)	(.00)
IT/process-oriented strategy	.026***	//	.020***	.000	-.002	-.002	.018**	-.002
	(.01)		(.01)	(.00)	(.00)	(.00)	(.01)	(.00)
Process/product-oriented strategy	.015**	//	.019***	.002	-.001	-.001	.013**	-.001
	(.01)		(.01)	(.00)	(.00)	(.00)	(.01)	(.00)
IT/product-oriented strategy	.024***	//	.014**	.007**	.006*	.008**	.013**	.006*
	(.01)		(.01)	(.00)	(.00)	(.00)	(.01)	(.00)
Factor input								
Capital income per employee (log)	//	//	//	.381***	.378***	.378***	//	.378***
				(.00)	(.00)	(.00)		(.00)
Share of academics (%, log)	//	//	//	.024***	.018***	.022***	//	.018***
				(.00)	(.00)	(.00)		(.00)
Share of other tertiary diplomas (%, log)	//	//	//	.023***	.021***	.023***	//	.021***
				(.00)	(.00)	(.00)		(.00)
R&D expenditures per employee (log)	//	//	//	-.003	-.002	//	//	//
				(.00)	(.00)			
Firm and industry heterogeneity								
Number of employees (log)	//	//	//	//	.016***	.016***	.013***	.017***
					(.00)	(.00)	(.00)	(.00)
The firm is foreign-owned (yes/no)	//	//	//	//	.057***	.059***	.018***	.060
					(.00)	(.01)	(.02)	(.01)

Table 10 (continued)

Table 10 (continued)

The firm is less than ten years old (yes/no)	//	//	//	//	.021* (.01)	.024* (.01)	//	//
Technological/innovation potential [c]	//	//	//	//	.008 (.01)	//	//	//
The firm is exporting goods/services (yes/no)	//	//	//	//	.019** (.01)	//	.084*** (.01)	.019** (.01)
More than five but less than ten principal competitors worldwide (yes/no)	//	//	//	//	.013** (.01)	.012* (.01)	//	//
Industry affiliation								
28 industry dummies (2-digit)	//	Yes	Yes	Yes	Yes	Yes [d]	Yes	Yes
Time dummies								
3 year dummies (reference 1999	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics								
Number of observations	4964	4964	4964	4964	4964	4964	4964	4964
F-value	16***	41***	38***	396***	355***	411***	41***	388***
Adjusted R2	.024	.201	.210	.761	.766	.763	.246	.766

[a] 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. [b] Cluster affiliation is measured by the firms' factor scores used as input for the cluster analysis that served to identifying the modes of innovation. [c] The technological/innovation potential in and around a firm's fields of activity is measured on a five-point ordinal scale, with value 1 representing the scores 4 or 5 (high potential) and value 0 otherwise (low potential). [d] In this model, the dummies for five industries that are highly R&D-intensive are excluded (chemicals/pharmaceuticals, non-electrical machinery, electrical machinery, electronics/instruments, R&D/IT-services), as they quite strongly correlate with the science-based strategy and the human capital intensity (percentage share of academics and of other tertiary diplomas).

strategies and/or their industry affiliation. These estimates neglect the impact of the use of production inputs and the heterogeneities at firm and industry level. In column 4, we extend model 3, which takes account of the innovation strategies *and* industry affiliation, by adding four factor input variables (production function). In column 5, we provide the estimates for the "full model" that contains all variables we specified in in the previous subsection (model 5). Column 6 shows the results for the final equation (model 6), where we deleted some variables, due to problems of variable specification, endogeneity or collinearity. In addition, we present in the columns 7 and 8, the results from estimating two models (model 7 and 8) that allow a *comparison* of the results with those of previous studies (see subsection 6.3).

Model 1 (Table 10, column 1) includes, in addition to three time dummies, only the five 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 effect. However, the overall effect is weak, as indicated by the low value of the adjusted R^2. The process/product-oriented strategy contributes least to productivity. The impact on productivity is substantially larger in the case of the science-based strategy and the IT/process-oriented strategy. To a lesser extent, this also is true for the IT/product-oriented strategy, whereas the productivity effect of the investment-based strategy is of "intermediate size". 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 this model, with the exception of the three time dummies, only includes the variables that capture the five innovation strategies.

In *model 2* (Table 10, column 2), we only include 28 *industry dummies* (2-digit level). Again, we do not take into account the impact of the factor inputs and the heterogeneities at firm and industry level. We find that the industry dummies are *jointly significant*. This model explains 20% of total variance.

In *model 3* (Table 10, column 3), we insert *both* the five *innovation strategies and* the 28 dummy variables representing *industry affiliation*. We find that both categories of variables exert a statistically significant influence on productivity. Moreover, the contribution to productivity due to the choice of specific innovation strategies does not too much differ from the corresponding impact according to model 1 that does not include the industry dummies. The productivity effect of the two sets of variables is thus more or less independent. However, a comparison of the adjusted R^2 of the models 1, 2 and 3 reveals that industry affiliation (joint effect of all industry dummies), by far, is more relevant for explaining firm performance than the five innovation strategies. We find an adjusted R^2 of 0.21 for model 3 (both sets of variables) and 0.20 for model 2 (industry dummies only), whereas the adjusted R^2 for model 1 (innovation strategies only) is very low, i.e., 0.02.

Altogether, the estimates of the models 1 to 3 show that the impact of industry affiliation is substantially larger than that of the five innovation strategies. However, this *assessment* of the relative importance of innovation strategies and industry affiliation as factors determining a firm's labour productivity is *only tentative*, as the three models do not take into account the productivity effect of the use of the production inputs (production function) and the heterogeneities at firm and industry level.

In *model 4* (Table 10, column 4), we add to model 3 four variables that capture the effect on productivity attributed to the intensity of use of the production inputs *physical capital, human* *capital and knowledge capital (R&D)*. We find that physical capital intensity and (the two dimensions of) human capital intensity are statistically significant, which is not the case for the R&D intensity. The latter result is not surprising as R&D intensity and human capital intensity are highly correlated. Moreover, the estimates reveal that the productivity effect of the innovation strategies, in comparison to model 3, is substantially lower. Only two of the five innovation strategies remain statistically significant as soon as we include the variables representing the production factors (as against five in case of model 3). The extended model 4 explains 76% of the total variance compared to 21% in the case of model 3. A substantial part of the difference is due to the physical capital variable. In view of the high relevance of the physical capital intensity, we checked the robustness of this result by using the "investment to labour ratio" as an alternative measure. As the findings using this specification do not much differ, we conclude that the results with respect to the physical capital intensity are robust.

Model 5 (Table 10, column 5) includes *all categories of variables* which, according to subsection 6.1, are supposed to have an effect on labour productivity ("full model"): innovation strategies, production inputs, heterogeneities at firm and industry level and, finally, industry dummies. It turns out that the *impact of the innovation strategies on productivity further decreases* (compared to model 4) as only one of the five innovation strategies yields a statistically significant contribution to labour productivity (IT/product-oriented strategy). The effect of the *production inputs* hardly changes. Turning to the firm and industry heterogeneities, which are the new element of model 5, we find, as expected, that *firm size, foreign-ownership* (yes/no) and *young firm* (less than ten years old, yes/no) are characteristics of a company that positively correlate with labour productivity. Furthermore, we find, as hypothesised, that an *intermediate degree of competition* on the product market is a particularly favourable market environment for raising productivity. The influence of *industry affiliation* remains strong, although it is not of the same magnitude as in the models 3 and 4.

In contrast, we do not find a significant influence of the variable "*innovation capacity*" (approximated by a firm's technological/innovation potential). This result might reflect the correlation of this variable with some of the innovation strategies, particularly, but not only, the science-based strategy. Besides, we get a statistical significant (positive) effect for a firm's *export propensity* (and, alternatively, for the export intensity, i.e. the export to sales ratio). However, Wagner (2012) surveying a large number of studies shows that there is a two-way relationship between exporting and productivity. The causality runs from exports to productivity (reflecting the effect of learning from being active abroad), but it also runs in the opposite direction (high productivity as a precondition for compensating the costs of entering foreign markets). Consequently, the export variable is endogenous. As the majority of the surveyed studies finds that the causal link running from productivity to exports is dominant, our results do not confirm the proposition of a positive productivity effect of exporting. The use of the "size of foreign markets" as an export variable would overcome the problem of endogeneity; however, our dataset does not provide such information.[19]

[19] Following an alternative method to correct for endogeneity (see Cassiman and Veugelers 2002), we calculated the average export intensity at the *3-digit industry level* and inserted these values as measures for the export intensity of the *individual firms affiliated to the corresponding 3-digit industry*. However, the results with respect to the productivity effect of exporting does not much differ from those shown in Table 10.

Given the problems with estimating model 5, we specify a final equation (*model 6*), where we delete four (problematic) variables: (a) R&D intensity, (b) innovation capacity, (c) export propensity, and (d) five dummies that capture a firm's affiliation to selected high-tech industries (see the last footnote of Table 10). Multicollinearity is a problem in the case of (a), (b), and (d), whereas endogeneity is an obstacle to get reliable estimates for (c). A comparison of the results for model 6 and model 5 shows that the productivity effect of the variables contained in both models is very similar, and the model fit is largely the same. Finally, based on a more in-depth analysis, we find that industry affiliation is clearly more relevant in explaining the firms' productivity than the choice of a specific innovation strategy. According to model 6, only one strategy provides a productivity premium, i.e., the IT/product-oriented innovation strategy. The finding of a much weaker effect of the strategy variables compared to that of the industry dummies is in line with the results of the estimates of the models 3 to 5, although the relevance of the industry affiliation is not anymore as accentuated as before.

6.3 Comparison with earlier studies

To the best of our knowledge, there are only four studies dealing with the relationship between innovation modes (strategies) and firm performance (labour productivity) that are more or less comparable.[20] These investigations throughout are based on data from one single cross-section, which implies, as already mentioned, that the explanatory variables, in principle, may be endogenous.

Hollenstein (2003) uses a model that is quite similar to the present one. His model contains largely the same (four) categories of variables, i.e., (a) a set of innovation strategies, (b) the input factors of a production function, (c) variables representing firm level (but no industry level) heterogeneities, and (d) industry affiliation (dummies). The estimates of this model are based on a sample of *services* firms. According to this study, the relationship between the innovation strategies and labour productivity is weak (as it is in the present paper); only one (out of five) innovation strategy is statistically significant ("IT-oriented network-integrated firms emphasising product development"). To improve the comparability of the results, we re-estimate our model for the subsample of services firms. In so doing, we obtain a statistically significant effect on productivity for the "IT/product-oriented innovation strategy". The results of the two studies are thus quite similar, although the innovation strategies identified in the two studies are not fully the same.

The other three studies (Frenz and Lambert 2009, 2012; Sanchez 2014) apply a model that captures (a) the innovation strategies, (b) some heterogeneities at firm- and industry level, and (c) the firms' industry affiliation. The specification of the three categories of variables slightly

[20] We do not compare our results with Roud (2018), although the econometric productivity model used by this researcher, i.e. the multi-step CDM model developed by Crépon et al. (1998), is (econometrically) superior to our approach. As Roud (2018) relies on an *ex ante-definition of innovation modes* ("top-down approach"), which is based on simple a priori-classification rules, the preconditions for a reliable comparison are not satisfied (see subsection 3.4). Moreover, his paper does not allow an assessment of the relative merits of the "strategic management concept" and the "technological regime approach", as it does not provide an analysis of the intra-industry variance of innovation modes.

differs from our model, but the divergences do not really matter. The most important difference refers to the fact that these researchers neglect the productivity effect of the use of the production inputs, which, from a theoretical point of view, is a serious deficiency. Frenz and Lambert (2012),[21] 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. In contrast, Sanchez (2014) finds a significant impact on productivity for each strategy (five strategies). However, this study may overestimate the strategy effects, as the underlying model contains only a sector dummy (manufacturing yes/no), whereas the other papers use a large number of 2-digit industry dummies.

The specification of the models used in the two studies, as already mentioned, is not adequate, as it does not account for the productivity effect of the classical factor inputs. Therefore, to get a more reliable comparison with our results, we *estimate with Swiss data* a productivity model based, as far as possible, on the *specification used by Frenz and Lambert (2012)*. We thus delete from our model the variables that capture the use of physical, human and R&D capital. Moreover, we take into account only firm and industry heterogeneities that are contained both in Frenz and Lambert (2012) and the present paper.

Model 7 (Table 10, column 7) shows for Switzerland that, in this specification, *all* innovation strategies exert a statistically significant influence on firm productivity. This result is in line with Sanchez (2014),[22] but differs from the findings reported by Frenz and Lambert (2012), which get, for the majority of countries, a significant productivity effect only for one or two (out of five) innovation strategies. *Model 8* (Table 10, column 8) shows, based on Swiss data, that the positive impact of the five innovation strategies disappears, with one exception ("IT/product-oriented strategy"), as soon as we use the theoretically well founded model that includes the factor input variables. We cannot see any reason why the same should not happen in estimates for other countries as well, if these would be based on a correctly specified model, i.e., one that includes the factor inputs. Therefore, we conclude, by analogy, that the much stronger effects of the innovation strategies (compared to what we find) identified by Sanchez (2014) for US companies, and, to a lesser extent, by Frenz and Lambert (2012) for eight (out of fifteen) OECD countries, primarily are due to a misspecification of the empirical productivity model.

6.4 Model estimates differentiated by productivity level

The model estimates presented in Subsection 6.2 imply that the "technological regime approach" is superior to the "strategic management view" as a framework to analyse the innovation behaviour of firms. The evidence for positive productivity effects of firm-specific innovation strategies is weak. Only one out of five strategies provides a productivity premium, whereas industry affiliation clearly has a positive effect on productivity. However, this con-

[21] In the following, we only refer to Frenz and Lambert (2012), as their 2009 paper is largely a first (very similar) version of the more recent study.

[22] For Switzerland, 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.

clusion neglects that the *productivity level* of industries and firms, to some extent, may be *historically given* because of *path dependences* with respect to technology, the fields of activity, market dynamics, etc. Therefore, the model estimates presented in subsection 6.2 may not be the most appropriate way of dealing with the basic question of the relative merits of the two concepts for analysing the innovation behaviour of firms.

Against this background, we *estimate model 6* (as specified in Table 10) *separately for firms characterised by different productivity levels*. More specifically, we perform estimations for *five subgroups of firms (quintiles*) representing different levels of productivity (1st quintile: very low productivity; 5th quintile: very high productivity).[23] The results of these regressions show that the impact of the innovation strategies on firm performance is not homogeneous among the productivity quintiles (see Table 11). Firms with very low productivity (1st quintile) earn a productivity premium by choosing an "investment-based innovation strategy", whereas companies with an intermediate productivity level do so by pursuing an "IT/product-oriented strategy", and "very high-productivity firms" improve their competitive position by choosing an "IT/process-oriented strategy". In contrast, we do not find any significant productivity effect of a specific innovation strategy for the firms of the second and the fourth quintile. For this reason, and because the success of the firms belonging to the other three quintiles is based in each case on a different strategy, it is not particularly surprising that, for the whole sample, we do not find a significant productivity effect of the strategy variables, with the exception of the "IT/product-oriented strategy".

The results imply that the optimal choice of an innovation strategy depends, though only in some instances, on the prevailing level of productivity (path dependence). The estimates based on the whole sample thus conceal some differences with respect to the productivity effect of the five innovation strategies. The divergences among the five subgroups (quintiles) with respect to the optimal strategy may reflect differences with respect to the availability of strategic resources and or the innovation-related environment. For example, the firms with very low productivity (1st quintile) may not be able to generate innovations based on internal resources but tend to *adopt* novelties developed by other companies or research institutions. Accordingly, an investment-based strategy is the most promising one. Quite surprisingly, "very high-productivity firms" (5st quintile), which earn a productivity premium by pursuing an "IT/process-oriented strategy", do not combine this innovation mode with a "science-based strategy". Besides, it is remarkable to what extent the model fit for the most productive firms (5st quintile) is superior to that of the other quintiles (see Table 11, column 3). "Very high-productivity firms" seem to profit from particularly favourable conditions with respect to their capabilities and the innovation-related environment.

Furthermore, it turns out that the productivity effect of industry affiliation is larger than the effect of the choice of specific innovation strategies only in two subsamples (1st and 5th quintile), whereas the estimates based on the whole sample indicate a clear dominance of industry effects. In view of these mixed results, it is not as clear as suggested by the results we reported on in the previous subsection (total sample), that the "technological regime approach"

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23 We renounce to performing "quantile regressions" as our more simple approach based on a preselected number of subgroups (quintiles) suffices to get an impression of the heterogeneity of the productivity effect of the five specific innovation strategies.

("homogeneity hypothesis") is more appropriate than the "strategic management view" (heterogeneity hypothesis). However, as the attenuation of the industry effects by taking account of the prevailing (to some extent, historically given) productivity level is not particularly pronounced, we still may conclude that the results primarily support the "technological regime approach".

Table 11: Relationship between innovation strategies [a] and labour productivity (log): Differentiation by *productivity level*
(Pooled data 1999, 2002, 2005 and 2008; OLS estimation of model 6 shown in Table 10)

	Significant strategy [b, c]	Number of observations	Adjusted R^2
Productivity level			
Very low (1st quintile)	2*	986	.210
Low (2nd second quintile)	ns.	999	.049
Intermediate (3rd quintile)	5*	993	.093
High (4th quintile)	ns.	993	.137
Very high (5th quintile)	3*	993	.673
All firms (see Table 10, model 6)	5**	4964	.763

[a] Strategy 1: "Science-based Strategy". Strategy 2: "Investment-based strategy". Strategy 3: "IT/process-oriented strategy". Strategy 4: "Process/product-oriented strategy". Strategy 5: "IT/product-oriented strategy". [b] The results represent estimates of model 6 (see Table 10) that includes, in addition to the five innovation strategies the following variables: physical capital intensity, human capital intensity, firm size, foreign ownership of the firm, firm age, degree of competition, and industry affiliation (five dummies representing highly R&D intensive industries are excluded; see Table 10, footnote d). [c] The significance of the parameters is indicated with ***, ** and * resp. representing the 1%, 5% and 10%-level.

6.5 Assessment of the results

Altogether, the results in this section 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 innovation strategies at the firm level providing a competitive edge. However, the degree of freedom is rather limited as we find that only one of the five strategies yields a small productivity premium. The empirical results are thus primarily in line with the *technological regime approach*. On the other hand, we find that, depending on the prevailing (historically given) productivity level, some of the innovation strategies seem promising to improve a firm's competitive position. The evidence supporting the technological regime approach is thus not as accentuated as the estimates based on the whole sample suggest.

We remind that the empirical results with respect to the "intra-industry heterogeneity of innovation strategies" (see Section 5), primarily support the *strategic management view*. In that section, however, we also argued that the evidence with respect to the intra-industry heterogeneity might not be strong enough to clearly rejecting the technological regime approach. Given the contradictory results we find in the Sections 5 and 6, we conclude that the evidence does not allow to unambiguously discriminating between the two approaches. Moreover, we 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 seeking to create a competitive advantage *("strategic management view"*). 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 applying 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 previous research. This first element of the analysis provides the basis for the subsequent 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. Moreover, on this basis, we are able to assess whether the observed switches between innovation strategies are in line with the requirements of the structural change in a highly advanced economy such as the Swiss one. *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 the exception of Leiponen and Drejer (2007), 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 innovation strategies and industry affiliation as variables to explaining firm performance we provide additional insights into the appropriateness of the two approaches. To this end, we econometrically estimate a productivity equation based on four sets of explanatory variables: the innovation strategies, the classical inputs of production, heterogeneities at firm and industry level, and industry dummies. In so doing, we also account for a possible path dependence of the current productivity level. Surprisingly, previous studies dealing with this topic, with the exception of Hollenstein (2003), did not account for the use of the production inputs, 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, depending on the type of analysis, between 4964 and 5645 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 a firm's innovation performance. The five strategies are: (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. 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 often identified two strategies similar to (a) and (b), but, quite remarkably, they never found an IT-oriented strategy like (c) or (e). Although this may be due to a lack of data, it is a serious deficiency in view of the technological trends in the last three decades.

Secondly, we find that a *large share of the firms modifies the 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 highly innovative firms, are the "net winners" from the shifts of strategies. In these three 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 (the "outflows" are larger than the "inflows") are the companies pursuing the least innovative strategy, i.e. the process/product-oriented strategy (d). This pattern of the dynamics of the firms' innovation strategies is 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. The findings further confirm the adequacy of the five innovation modes identified in the first part of the study.

Thirdly, a large number of the 4-digit industries, which should be more or less homogenous in terms of their production activities, is characterised by a *high degree of heterogeneity in terms of the innovation strategies* pursued. The share of industries appearing in at least four innovation clusters is very large, 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 sufficiently strong 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 (Leiponen and Drejer 2007), which unambiguously favours the heterogeneity hypothesis.

Finally, econometric estimates show that the *impact of the firms' innovation strategies on labour productivity is weak, and clearly smaller than industry effects* (having controlled for the classical inputs of production and for heterogeneities at firm and industry level). Only the IT/product-oriented strategy provides a productivity premium. These findings primarily support the "technological regime approach" (homogeneity hypothesis). The results are in line with the only study that is methodologically convincing, as it (also) uses a production function framework (Hollenstein 2003). However, by taking into account that the productivity level may be partly historically given (path dependence), the dominance of the technological regime approach, to a certain extent, becomes less accentuated.

The evidence reported on in the last two paragraphs remains contradictory. We interpret the findings as follows: On the one hand, as postulated by the strategic management view, the *firms have a certain room of manoeuvre to implement a specific innovation strategy*, reflecting their particular capabilities and the prevailing level of productivity (path dependence). On the other hand, in line with the technological regime approach, some *structural characteristics at the aggregate level* (technological opportunities, etc.) *restrict the strategic options of the individual company*, as industry affiliation exerts a stronger effect on productivity than the firms' innovation strategies. Altogether, the results imply that the *two concepts of the firms' innovation behaviour are complements rather than substitutes*, whereas previous research, perhaps with the exception of Peneder (2010), clearly prefers either the one or the other interpretation.

Each part of the 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 factors determining, according to the "economics of innovation, a firm's innovation activity. *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 rests almost exclusively on 2-digit industry data. *Fourthly*, the study is practically the only one that uses a theoretically adequate model to determine empirically the relative importance of the firms' innovation strategies 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 a framework for analysing the innovation behaviour of firms. We conclude, as mentioned above, that the two approaches are complements rather than substitutes.

The study has a number of *limitations* giving rise to some *proposals for future research*. *Firstly*, the dataset only includes information up to 2008. In view of the distinct and ongoing structural change of the economy (rapid technological change, globalisation of business activities, etc.), an analysis with more recent data may have provided additional insights.

However, we could not go beyond 2008, as the questionnaire of the Swiss Innovation Surveys used later on was no longer comparable. *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 in the short run. *Thirdly*, the dynamic analysis 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. Candidates for such variables explaining switches of innovation strategies could be, for example, a technology-push, a demand shift or a change of type and intensity of competition. *Fourthly*, due to the cross-section nature of the data, we have to interpret the results with respect to the effect of a firm's innovation strategy and industry affiliation on firm performance as conditional correlations rather than causal relationships. Nevertheless, as our model underlying the econometric analysis is theoretically well established, we assert that we still are able to assess the extent to which the empirical results are consistent with the "strategic management view" or the "technological regime approach". Nevertheless, an econometric investigation of this topic based on longitudinal data would be highly welcome. *Finally*, it would be worthwhile to estimate a performance equation applying as dependent variable, instead of labour productivity, a measure that is closer to the innovation process. A candidate would be the "sales share of innovative products", which implies, however, that one would have to exclude this variable from the set of innovation indicators used in this research to identifying innovation modes.

References

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W.R. Kerr (2018). Innovation, Reallocation, and Growth. *American Economic Review* 108(11): 3450–3491. https://www.aeaweb.org/articles?id=10.1257/aer.20130470

Aghion, P., A. Bergeaud, M. Lequien, and M.J. Melitz (2018). The Impact of Exports on Innovation: Theory and Evidence, *NBER Working* Paper 24600. National Bureau of Economic Research: Cambridge (MA). https://www.nber.org/papers/w24600

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005). Competition and Innovation: An Inverted-U Relationship, *Quarterly Journal of Economics* 120(2): 701–728. https://dash.harvard.edu/handle/1/4481507

Archibugi, D.S. (2001). Pavitt's Taxonomy Sixteen Years On: A Review Article. *Economics of Innovation and New Technology* 10(5): 415–425. https://dx.doi.org/10.1080/10438590100000016

Arvanitis, S., and H. Hollenstein (1994). Demand and Supply Factors in Explaining the Innovative Activity of Swiss Manufacturing Firms. *Economics of Innovation and New Technology* 3(1): 15–30. http://dx.doi.org/10.1080/10438599400000001

Arvanitis, S., and H. Hollenstein (2001). Innovative Activity and Firm Characteristics. A Cluster Analysis of Swiss Manufacturing Using Firm-level Data. In OECD (Ed.). *Innovative Networks: Co-operation in National Innovation Systems*: pp. 48–76. OECD: Paris.

Breschi, S., F. Malerba, and L. Orsenigo (2000). Technological Regimes and Schumpeterian Patterns of Innovation. *Economic Journal* 110(463): 388–410. http://www.jstor.org/stable/2566240

Cassiman, B. and R. Veugelers (2002). R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium. *American Economic Review*, 92(4): 1169–1184. https://www.aeaweb.org/articles?id=10.1257/00028280260344704

Castellacci, F. (2008). Technological Paradigms, Regimes and Trajectories: Manufacturing and Service Industries in a New Taxonomy of Sectoral Patterns of Innovation. *Research Policy* 37(6/7): 978–994. https://doi.org/10.1016/j.respol.2008.03.011

Cesaratto, S., and S. Mangano (1993). Technological Profiles and Economic Performance in the Italian Manufacturing Sector. *Economics of Innovation and New Technology* 2(3): 237–256. http://dx.doi.org/10.1080/10438599300000005

Chang, Y-C., and M.-N. Chen (2016). Service Regime and Innovation Clusters: An Empirical Study from Service Firms in Taiwan. *Research Policy* 45(9): 1845–1857. https://doi.org/10.1016/j.respol.2016.06.001

Chesbrough, H.W. (2003). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Harvard Business School Press: Cambridge (Mass.).

Cohen, W.M. (1995). Empirical Studies of Innovative Activity. In P. Stoneman (Ed.). *Handbook of the Economics of Innovation and Technological Change*: pp. 182–264. Oxford University Press: Oxford.

Cohen, W.M. (2010). Fifty Years of Empirical Studies of Innovative Activity and Performance. In B.H. Hall and N. Rosenberg (Eds.). *Handbook of the Economics of Innovation*, vol. 1: pp. 129–213. North Holland: Amsterdam. https://doi.org/10.1016/S0169-7218(10)01004-X

Cohen, W.M., and D.A. Levinthal (1989). Innovation and Learning: The Two Faces of R&D. *Economic Journal* 99(397): 569–596. http://www.jstor.org/stable/2233763

Crépon, B., E. Duguet, and J. Mairesse (1998). Innovation and Productivity: An Econometric Analysis at the Firm Level. *Economics of Innovation and New Technology* 7(2): 115–158. https://doi.org/10.1080/10438599800000003

De Jong, J.P.J., and O. Marsili (2006). The Fruit Flies of Innovations: A Taxonomy of Innovative Small Firms. *Research Policy* 35(2): 213–229. https://doi.org/10.1016/j.respol.2005.09.007

Dosi, G. (1982). Technological Paradigms and Technological Trajectories: A Suggested Interpretation of the Determinants and Directions of Technical Change. *Research Policy* 11(3): 147–162. https://doi.org/10.1016/0048-7333(82)90016-6

Dosi, G. (1988). Sources, Procedures, and Microeconomic Effects of Innovation. *Journal of Economic Literature* 26(3): 1120–1171. http://dimetic.dime-eu.org/dimetic_files/DosiJEL1988.pdf

Evangelista, R. (2000). Sectoral Patterns of Technological Change in Services. *Economics of Innovation and New Technology* 9(3): 183–222. http://dx.doi.org/10.1080/10438590000000008

Frenz, M., and R. Lambert (2009). Exploring Non-technological and Mixed Modes of Innovation Across Countries. In OECD (Ed.). *Innovation in Firms: A Microeconomic Perspective*: pp. 69–110. OECD: Paris. http://www.oecd-ilibrary.org/science-and-technology/innovation-in-firms_9789264056213-en

Frenz, M., and R. Lambert (2012). Mixed Modes of Innovation: An Empirical Approach to Capturing Firms' Innovation Behaviour. OECD Science, Technology and Industry Working Papers 2012/06. OECD: Paris. http://dx.doi.org/10.1787/5k8x6l0bp3bp-en

Hollenstein, H. (2003). Innovation Modes in the Swiss Service Sector: A Cluster Analysis Based on Firm-level Data. *Research Policy* 32(5): 845–863. https://doi.org/10.1016/S0048-7333(02)00091-4

Jensen, M.B, B. Johnson, E. Lorenz, and B.A. Lundvall (2007). Forms of Knowledge and Modes of Innovation. *Research Policy* 36(5): 680–693. https://doi.org/10.1016/j.respol.2007.01.006

Kaufmann, H., and H. Pape (1996). Clusteranalyse. In L. Fahrmeir, A. Hamerle, and G. Tutz (Eds.). *Multivariate statistische Verfahren*, 2nd Edition: pp. 437–536. De Gruyter: Berlin-New York.

Knott, A.M. (2003). Persistent Heterogeneity and Sustainable Innovation. *Strategic Management Journal* 24(8): 687–705. http://www.jstor.org/stable/20060569

Kogut, B., and U. Zander (1993). Knowledge of the Firm and the Evolutionary Theory of the Multinational Corporation. *Journal of International Business Studies* 24(4): 625–645. http://www.jstor.org/stable/155168

Leiponen, A., and I. Drejer (2007). What Exactly are Technological Regimes? Intra-industry Heterogeneity in the Organization of Innovative Activities, *Research Policy* 36(8): 1221–1238. https://doi.org/10.1016/j.respol.2007.04.008

Malerba, F., and L. Orsenigo (1993). Technological Regimes and Firm Behaviour. *Industrial and Corporate Change* 2(1): 45–71. https://doi.org/10.1093/icc/2.1.45

Malerba, F., and L. Orsenigo (1997). Technological Regimes and Sectoral Patterns of Innovative Activities. *Industrial and Corporate Change* 6(1): 83–118. https://doi.org/10.1093/icc/6.1.83

Manly, B.F.J. (1986). *Multivariate Statistical Methods. A Primer*. Chapman and Hall: London.

McGahan, A.M., and M.E. Porter (1997). How Much Does Industry Matter, Really? *Strategic Management Journal* 18 (Special Issue): 15–30. http://www.jstor.org/stable/3088208

Miozzo, M., and L. Soete (2001). Internationalization of Services: A Technological Perspective. *Technological Forecasting and Social Change* 67(2/3): 159–185. https://doi.org/10.1016/S0040-1625(00)00091-3

Nelson, R.R., and S.G. Winter (1977). In Search of a Useful Theory of Innovation. *Research Policy* 6(1): 36–76. https://doi.org/10.1016/0048-7333(77)90029-4

Nelson, R.R., and S.G. Winter (1982). *An Evolutionary Theory of Economic Change*. Harvard University Press: Cambridge (Mass.).

OECD (2008). Handbook on Constructing Composite Indicators. Methodology and User Guide. OECD: Paris.

Pavitt, K. (1984). Sectoral Patterns of Technical Change: Towards a Taxonomy and a Theory. *Research Policy* 13(6): 343–373. https://doi.org/10.1016/0048-7333(84)90018-0

Peneder, M. (2010). Technological Regimes and the Variety of Innovation Behaviour: Creating Integrated Taxonomies of Firms and Sectors. *Research Policy* 39(3): 323–334. https://doi.org/10.1016/j.respol.2010.01.010

Roud, V. (2018). Understanding the Heterogeneity of Innovation Modes: Performance Effects, Barriers, and Demand for State Support. *Technological Forecasting and Technological Change* 133: 238–253. https://doi.org/10.1016/j.techfore.2018.04.025

Rubin, D.B. (1987). *Multiple Imputation for Nonresponse in Surveys*. Wiley: New York.

Rumelt, R.P. (1991). How Much does Industry Matter? *Strategic Management Journal* 12(3): 167–185. http://www.jstor.org/stable/2486591

Sanchez, J. (2014). Non-technological and Mixed Modes of Innovation in the United States: Evidence from the Business Research and Development and Innovation Survey, 2008–2011. *US Census Bureau, Center for Economic Studies Paper* CES-WP 14-35. US Census Bureau: Washington (DC). https://ideas.repec.org/s/cen/wpaper.html

Srholec, M., and B. Verspagen (2012). The Voyage of the Beagle into Innovation: Explorations on Heterogeneity, Selection, and Sectors, *Industrial and Corporate Change* 21(5): 1221–1253. https://doi.org/10.1093/icc/dts026

Teece, D.J. (2010). Technological Innovation and the Theory of the Firm: The Role of Enterprise-level Knowledge, Complementarities, and (Dynamic) Capabilities. In B.H. Hall and N. Rosenberg (Eds.). *Handbook of the Economics of Innovation*, vol. 1: pp. 679–730. North Holland: Amsterdam. https://doi.org/10.1016/S0169-7218(10)01016-6

Teece, D.J., G. Pisano, and A. Shuen (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal* 18(7): 509–533. https://www.jstor.org/stable/3088148

Tiri, M., L. Peeters, and G. Swinnen (2006). Innovation Patterns in Manufacturing and Services: Sectoral Determinism or Strategic Choice? A Multivariate Analysis of CIS-3 Data. *KIZOK, Research Centre for Entrepreneurship and Innovation*, Research Paper, Hasselt University: Hasselt-Diepenbeek (Belgium). https://www.researchgate.net/publication/279502655

Utterback, J.M., and W.J. Abernathy (1975). A Dynamic Model of Process and Product Innovation. *OMEGA: The International Journal of Management Science* 3(6): 639–656. https://doi.org/10.1016/0305-0483(75)90068-7

Wagner, J. (2012). International Trade and Firm Performance: A Survey of Empirical Studies since 2006. *Review of World Economics* 148(2): 235–267. https://doi.org/10.1007/s10290-011-0116-8

Wernerfelt, B. (1984). A Resource-based View of the Firm. *Strategic Management Journal* 5(2): 171–180. https://www.jstor.org/stable/2486175

Winter, S.G. (1984). Schumpeterian Competition in Alternative Technological Regimes. *Journal of Economic Behavior & Organization* 5(3/4): 287–320. https://doi.org/10.1016/0167-2681(84)90004-0

Wziatek-Kubiak, A., E. Balcerowicz, and M. Peczkowski (2013). Differentiation of Innovation Strategies of Manufacturing Firms in the New Member States: Cluster Analysis on Firm Level Data. *Argumenta Oeconomica* 2(31): 117–149. https://www.researchgate.net/publication/305618814

APPENDIX

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

Sector / Industry	% of firms
Low-tech manufacturing	*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
High-tech manufacturing	*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
Construction	*5.6*
Knowledge-intensive services	*14.5*
Banking, insurance	5.8
R&D, IT, technical services	2.6
Other business services	5.9
Telecommunication	0.2
Other services	*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[a]

Innovation indicators	Science-based	Investment-based	IT/process-oriented	Process/ product-oriented	IT/product-oriented	Total
Input-oriented measures						
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 related to innovation and IT	19	23	40	13	54	27
- Market introduction of innovations	38	28	20	15	52	29
Output-oriented measures						
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
Market-oriented measures						
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

[a] 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 [a]

Innovation objectives	Science-based	Investment-based	IT/process-oriented	Process/ product-or.	IT/product-oriented	Total
Product innovation						
- 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
Process innovation						
- 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
Aggregate objectives (*factor analysis*: 3 factors)						
- 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

[a] The upper part of the table shows for every objective of innovation the share of firms with score 4 or 5 on a 5-point ordinal scale. For example, “replacing mature products” is an important or a very objective for 40% 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 [a]

Determinants of innovation	Science-based	Investment-based	IT/process-oriented	Process/ product-oriented	IT/product-oriented	Total
Demand side						
- 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 *five* principal competitors (%)	36	27	27	28	28	29
Supply side						
- 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

[a] 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 [a]

Knowledge sources / innovation network	Science-based	Investment-based	IT/process-oriented	Process/ product-or.	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

[a] 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-oriented	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 [a]
(*4-digit* classification; 153 industries with *at least 8 firms*)

NACE Rev. 1	Description	N	Share (%) of firms by cluster [a] 1	2	3	4	5
A.	**Industries with *clearly specified* activities**						
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	**50**	0
1571	Manufacture of prepared food for farm animals	8	13	25	13	25	25
1581	Manufacturing of bread, fresh pastry goods and cakes	25	8	**56**	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	**50**	0	25	13
1596	Manufacture of beer	10	30	20	20	10	20
1598	Manufacture of mineral waters soft drinks	9	22	**56**	0	22	0
1730	Finishing of textiles	13	15	31	0	38	15
1740	Manufacture of made-up textile articles (except apparel)	8	**50**	13	0	25	13
2010	Sawmilling and planing of wood; impregnation of wood	17	6	**82**	0	12	0
2020	Manufacture of veneer sheets; manufacture of plywood	9	33	**56**	11	0	0
2030	Manufacture of builders' carpentry and joinery	66	12	33	15	24	15
2112	Manufacture of paper and paperboard	8	**50**	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	**53**	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	**55**	27	0
2412	Manufacture of dyes and pigments	9	**67**	22	0	11	0
2414	Manufacture of organic basic chemicals (excl. other 4-digits of 241)	9	**56**	0	11	33	0
2416	Manufacture of plastics in primary forms	17	**53**	18	6	24	0
2420	Manufacture of pesticides and other agro-chemical products	9	**67**	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	**55**	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	**50**	0
2753	Casting of light metals	16	13	**50**	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)

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	**57**	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	**60**	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	**50**	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	**53**	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	**73**	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	**53**	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	**53**	0	29	0

Table A.3 (continued)

Table A.3 (continued)

3140	Manufacture of accumulators, primary cells and primary batteries	8	**62**	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	**50**	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	**59**	9
3662	Manufacture of brooms and brushes	8	13	38	0	**50**	0
4010	Production and distribution of electricity	69	4	35	36	14	10
4523	Construction of motorways, roads, airfields and sport facilities	16	13	**56**	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	**50**
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	**54**
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	**50**	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	**64**
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	**60**
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	**53**	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	**51**	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	**50**	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	**65**	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	**50**	20	10
7440	Advertising	9	0	0	**56**	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.	**Industries with *not clearly specified* activities**						
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	**50**	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	**56**	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	**50**	13
3663	Other manufacturing n.e.c.	9	11	**67**	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	**50**	6	6

[a] 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).

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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