J Evol Econ (2009) 19:675–700
DOI 10.1007/s00191-008-0118-4

REGULAR ARTICLE

Industry diversity and its impact on the innovation performance of firms

An empirical analysis based on panel data (firm-level)

Martin Woerter

Published online: 15 August 2008

Abstract This paper investigates empirically the impact of diversity on the innovation performance of a firm. We created a measure for diversity that mirrors differences in the resource base of firms within an industry and tested its impact in addition to more traditional factors such as technology-push, demand-pull, and firm-size, based on panel data stemming from three representative cross sectional surveys carried out in the years 1996, 1999, and 2002, respectively. In fact, diversity has a significant positive impact on the innovation intensity of firms and thus supports more theoretical findings in this area. We also find empirical evidence for the technology push and the demand pull hypotheses, as well as the importance of competition for innovation.

Keywords Diversity · Innovation performance · Evolution of industries · Jacobs externalities · Panel data

JEL Classification O30

1 Introduction

Economically modern and well developed societies heavily rely on the willingness and abilities of firms to innovate for at least two reasons: First, countries need to strengthen their innovativeness to remain competitive in the future in order to maintain employment and secure social peace in a so-called "globalized" economy. Second, societies are increasingly confronted

M. Woerter (✉)
ETH Zurich, KOF Swiss Economic Institute,
8092 Zurich, Switzerland
e-mail: woerter@kof.ethz.ch

with unexpected adverse consequences of the behavior of economic agents (e.g. environmental pollution, greenhouse effect, scarcity of natural resources). Therefore, the innovation potential of firms is important to provide timely solutions to these urgent problems. This is a necessary condition for the evolution of the economic system, since evolution means solving current problems (see Nelson 1995). Following the notion of competition within a Darwinian evolutionary model, what matters is the joint distribution of relevant differences in innovative behavior across firms. These differences are the necessary background upon which competitive selection takes place and on which the process of evolution depends (see Metcalfe and Miles 1994).

This investigation is motivated by the quest for better market circumstances in order to promote the innovation behavior of firms and thus to increase the likelihood of economic evolution, i.e. to find timely solutions to unexpected adverse results of well-planned actions. It aims at analyzing the main determinants of the successful innovations of firms. In addition to the more traditional determinants that focus on the Schumpeterian hypotheses, technology push factors and demand pull factors, an empirical measure for diversity of the market environment similar to some biological notions is formulated and empirically tested.

Following the investigations of Nelson and Winter (1982), it can be seen that economic evolution is driven by firm heterogeneity. Chiaromonte and Dosi (1993) showed through simulations that more identical agents lead to very little technical progress and long-term fall in aggregate income. Thus, it is assumed that a more diverse market environment fosters the innovation performance of firms in the respective market.

In fact, our empirical findings are in line with the just-mentioned investigations. Based on a comprehensive panel dataset for Switzerland, comprising three cross-sections (1996, 1999, 2002), it was found that firms embedded in a more diverse market environment have a better innovation performance than firms in more homogeneous markets.

What are some implications of these findings? First, the results show that micro-investigations of innovative behavior that rely on the concept of “representative agents” may be to some extent misleading, since it is heterogeneity in behavior rather than uniformity that provides incentives for innovation (see Chiaromonte and Dosi 1993). Second, and a more policy related implication is that more diverse markets facilitate market entry and thus promote competition, since entrants are likely to find some particular, new product niche that may challenge the markets of incumbents in a longer run (see Feldman and Audretsch 1999; Jacobs 1969).

This paper is organized as follows. In Section 2, the modelling framework is introduces. In Section 3, we focus on diversity measures and define diversity for the purpose of this paper. In Section 4, data are described, and in Section 5, we specify our empirical model based on the theoretical framework in Section 2. Section 6 shows the empirical results and, in Section 7, we summarize the results and derive some conclusions.

2 Modelling framework

2.1 Determinants of innovative behavior revisited

The empirical investigation of what promotes innovative behavior of firms mainly circulates around the following hypotheses: (a) the so-called Schumpeterian hypotheses (see Schumpeter 1912, 1975) focus on the meaning of firm size and market concentration on innovative behavior (see Cohen 1995; Cohen and Levin 1989); (b) the demand-pull thesis (see Schmookler 1966) emphasizes the observation that market conditions, size of the market and price development are very important; (c) the technology-push hypothesis (see Phillips 1966; Rosenberg 1976) states that supply factors related to the conditions for knowledge production are essential; (d) there are several hypotheses circulating around the importance of financial restrictions (see Nelson 1959), R&D risks and risk preferences of firms (see Mansfield 1968); (e) Dosi (1988) essentially enhanced the empirical view on essential factors for innovative behavior, by pointing to the importance of appropriability, partial tacitness, and variety of knowledge bases, uncertainty and technical opportunities.

These hypotheses have been operationalized in different ways and empirically tested in a number of investigations (see Cohen 1995). Concerning investigations based on CIS (Community Innovation Survey) or SIS (Swiss Innovation Survey),[1] the following empirical evidence has been derived. Arvanitis and Hollenstein (1996) found that demand-pull factors (to a weaker extent), and primarily supply-side factors (appropriability, technological opportunities) drive the innovation performance of Swiss manufacturing firms. Also, larger firms (with more than 200 employees) have a greater propensity to innovation than smaller ones. Raymond et al. (2004) found in the Dutch case (three waves of the Dutch Community Innovation Survey, i.e. CIS 2, 2.5, 3) that demand-pull factors are more important than technology-push factors in respect of the innovation output measure (share of innovative sales). The size effect is in this case negative. This is in line with the findings of Mairesse and Mohnen (2001), with the exemption of a positive size effect and the positive correlation with demand-pull factors that is restricted to low-tech firms. Janz et al. (2003) found also a negative size effect (for Germany), but no demand-pull or technology-push effect. In contrast, Crépon et al. (1998) did not detect any size effect, but found a positive demand-pull or technology-push effect. All these studies are based on data derived form the CIS for manufacturing firms. In sum, there is no clear empirical evidence for positive size effects. As to technology-push and demand-pull effects, one can see that they are significantly positive or not significantly related to the innovation performance of a firm. There has never been a negative sign detected.

[1] The SIS is very similar to the CIS.

2.2 Bounded rationality of firm behavior

We intend to add a further perspective to this discussion about important driving factors for innovation. Following Dosi (1988) at least to some extent, we want to put forward the hypothesis that not only the existence of single factors emphasized by investigations so far but also their diversity (or asymmetry) is relevant to innovative behavior. Why does this proposition make sense? Why, for example, could a "diverse" or more heterogeneous[2] industry be a more beneficial environment for innovations than a more homogeneous one?

The work of Nelson and Winter (1982) is an adequate starting point for analyzing the possible impact of diversity on the innovation behavior of firms. They put forward the proposition that economic evolution is driven by agents confronted with bounded rationality and uncertainty. Furthermore, agents dispose of different resources (see Wernerfelt 1984), such as technological competencies and knowledge, as a result of their past decisions and experiences. Based on these resources, they try to reduce existing complexity and uncertainty through routines (see Nelson 1995). Routines result from successful behaviors in the past, from the successful combination of firm resources. They symbolize goal-oriented learning and selection and, thus, applied routines are the best available procedure from the perspective of the firm. You can find routines in several fields, e.g. in production (certain combination of input factors), organizational circumstances and applied technologies. Routines are established through organizational measures, e.g. the way the R&D department is integrated into the firm.

Routines are bounded and can hardly be changed in the short-run. According to the "satisfying" principle of Simon (1956), routines are very seldom fundamentally questioned and remain unchanged even if the economic environment may suggest a quite different behavior (see Simon 1981). Furthermore the firm's knowledge base, its technology and learning abilities are also very often bound to prevailing paradigms (see Dosi 1988) or focused on a dominant design (see Utterback 1996), thus limiting the firm's ability to react upon or adapt to new market circumstances. A further restriction to unbiased perception of the economic environment and an argument for "path dependency" can be found in the personal rule dependent perception as it is analyzed in Holland et al. (1986). This way, important environmental signals, pointing at a change in behavior, may be overlooked or simply ignored, since they are not foreseen in the rule code of the firm and its staff. Or to put it differently, based on working routines, the members of an organization expect familiar signals from others and will respond in familiar ways (see Winter 2006);[3] newer information will be not perceived as a familiar signal and it will be ignored. In fact, learning is quite limited in the short-run and thus it

[2]The term "diversity" or "diverse" is motivated by the definition given in Section 3. Heterogeneous is used synonymously with diversity.

[3]Nelson (2006) comments on Winter (2006).

is very difficult to adapt working routines[4] immediately to changing market circumstances, even if firms find themselves exposed to a very competitive environment.

Acknowledging that firms reduce economic complexity through routines and that routines are bounded, it is clear that firms develop their own, individual understanding of what characterises efficient behavior. Thus, firms distinguish themselves from competitors through working routines and, based on these routines, they decide what information seems to be important for innovation and what information is unimportant. Certainly, routines are far from being perfect in a way that they could succeed in comprising all information and reducing it to efficient working procedures. In general, they cover only pieces of information. Imagine that newer information is produced by other economic actors and this information spreads in the market. Some firms immediately may see the importance of this information for future innovations. Other firms may also know about it but cannot detect any use. A third category of firms may even not perceive or process this information; they may be busy processing other information that in turn seems to be of no relevance for other firms (potential competitors). The point we want to make here is that, based on their routines, firms differ in their perceptions of what seems to be important for innovation. Based on their routines, firms differ in their problem perception and in their innovation behavior. Thus we may conclude that a more diverse sector ignores less and perceives more as a possible field for innovation, which increases the overall likelihood of innovations.

Understanding that firm behavior is based on routines that in turn are characterized by bounded rationality, that routines strongly differ between firms, and that learning is limited at least in the short-run, one can link it with the selection mechanism of competitive markets. Markets may select firms with adequate routines. Certainly other firms may learn to adapt their routines to meet changing market requirements, but they may be second, if there are other firms operating on working routines, technologies etc. that better fit with the changed market conditions.[5] Following the findings of Dosi (2005), we see that heterogeneity across firms will persist over time, notwithstanding the competitive process. Thus learning may help a firm to stay in the market, but most probably will not lead to very homogeneous types of firms; there will be firms with competitive disadvantages and lower profitability compared to firms with a better “fit.” Putting it another way, one may see that diversity shapes the adaptiveness of an industry to changing market requirements or changing demand, since there is a higher probability that there are already firms that can immediately comply with the changed circumstances, e.g. they invested

[4] As to challenges to implement or modify working routines in an organization see e.g. Lazaric and Denis (2005) or Pentland and Feldman (2005).

[5] Utterback (1996) describes the history of companies that were unable to change their innovation behavior, since they stuck to their “sunk” investments and technologies, although newer (better) technologies were already on the market.

in the right technology, have an adequate firm size to produce efficiently, or do research in niche markets that gain importance due to changed market circumstances. This means that their routines were less adequate in previous periods and they fit better now. Although usually longer lasting learning processes will take place and more and more firms may adapt more or less successfully to the newer market requirements, the new circumstances will be addressed immediately and more efficiently by already “fitting” firms. This fastens market adaptability to changing societal needs or challenges and, following Nelson (1995), this characterizes the evolution of markets.

2.3 The role of diversity for innovative behavior: some theoretical aspects

There are theoretical investigations on the impact of diversity of behavior on technological change showing that, based on a diffusion model, diversity is a necessary condition for the adoption of new technology. More clearly, Silverberg et al. (1988) stated that the overall diffusion process of a new technology is shaped by heterogeneous or diverse firm characteristics as to, e.g., firm size or skill levels. Thus, the likelihood of adopting a new technology depends on the skill level of the adopting firm and the level of skills generally available even to those firms not yet deploying the new technology. In turn the model indicates that the diffusion process shapes firm characteristics. As a consequence, new technologies or innovations seem to have an impact on diverse firm characteristics and those, in turn, impact the diffusion process.

Also Chiaromonte and Dosi (1993) stated in a theoretical model framework that firm specific decision rules, together with the history of innovation, imitation and learning by individual actors is responsible for permanent diversity. In fact, simulation results show that diversity among actors and as a consequence diverse economic behavior has a positive effect on the rate of innovation.

Llerena and Oltra (2002) created a model in order to investigate several aspects of diverse innovation strategies of firms. Innovation strategies are fixed rules reflecting bounded rationality and refer to the learning process of a firm. They distinguished cumulative (relying on internal knowledge) from non-cumulative firms (learning process is external) or strategies and they saw diversity of innovation strategies to be a source of good technological performance which leads to higher productivity levels compared to industries with homogeneous strategies. This means that, in the diverse case, the available technological spectrum is better used and it is also shown that, if we assume that strategies or different learning procedures are based on asymmetries in firm characteristics, we find some theoretical hint that industry diversity is an important condition for technological change or innovation.

Saviotti (1996) analyzed the implication of variety (defined as the number of distinguishable types of actors, activities and outputs required to characterize an economic system) for different economic concepts, such as international trade, competition, and technological life cycles. Basically it is seen that variety, technological evolution, and economic development are strongly related. Nguyen et al. (2005) built on the conceptual approach of Saviotti and Mani

(1995) and Saviotti (1996) and combined variety with niche theory, a theory of biological origin. The idea behind this approach seems to be that niches are likely to be created if markets grow faster. Niches are formed through the emergence of new and innovative products or improved existing products. Increasing the number of niches can be seen as an increase in variety. This provides space for innovative behavior and thus makes innovative products and the development of new technologies more likely, which in turn forms new niches or helps them to grow.

2.4 The role of diversity for innovative behavior: empirical evidence

Based on existing, comprehensive empirical investigations, essentially Jacobs (1969), externalities may be seen as an empirical operationalization of diversity that is close to our conceptual framework. Jacobs (1969) found that variety or diversity of industries promotes innovation and growth. Thus, a diverse knowledge environment, rather than similar knowledge and behavior of economic actors, fosters creativity, promotes market entry and competition for new ideas and, as a consequence, intensifies innovative behavior. Glaeser et al. (1992) largely confirmed the results of Jacobs, when they found that industries grow faster in cities with—relative to the national level—smaller firm size in an industry, and city-industries grow faster when the rest of the city is less specialized. Thus, a more heterogeneous industry structure as to firm size distribution fosters growth. Thus, one might assume that similar is true for the innovation performance.

Henderson et al. (1995) found empirical evidence for Jacobs's externalities only in the case of high-tech industries. Feldman and Audretsch (1999) linked diversity of economic activity to innovation output and found support for the diversity thesis in line with the Jacobs model. Also Greunz (2004) stated that the composition of industrial activity influences the innovation performance of the manufacturing sector, taking into account 153 European regions and 16 manufacturing sectors. European patent activities are also affected by Jacobs's externalities. Some of these studies also found empirical evidence for MAR (Marshall–Arrow–Romer) externalities. This concept is the contra hypotheses to Jacobs's externalities. MAR externalities mainly state that concentration rather than diversity promotes knowledge flows (spillovers) between firms and thus has a positive impact on the innovation performance of firms. Henderson et al. (1995) in the case of mature capital goods industries and Greunz (2004) as to European region patent activities, found some empirical evidence for MAR externalities as well.

Considering our modelling framework and recognizing that innovation is driven by problem perception and that problem perception depends on working routines that in turn are influenced by certain firm characteristics such as firm size, physical capital or R&D activities, one can argue that industries with more diverse firm characteristics would be relatively more innovative than industries with rather homogeneous ones. Based on these hypotheses, we investigate empirically the impact of diversity on the innovation performance of firms using a comprehensive data set (panel firm-level data). As just mentioned, there are empirical investigations on an industry-level contrasting the impact of specialization and diversity externalities on innovation performance. The study at hand differs from them in several respects. First, diversity is measured quite differently, focusing on distance measures (asymmetries in firm structures), thus enabling us to test the above mentioned conceptual framework. This way is used to address some shortcomings of related papers as detected by Llerena and Oltra (2002). They stated that many theoretical and empirical works reveal the limits of a concept of diversity that only linked to the variety (multitude) of products or endowments. Second, we use panel firm-level data that allows us at least to some extent to address the "causality" question (innovation promotes diversity or vice versa). Third, we have a number of control variables and variables addressing the more traditional hypotheses in addition to diversity.

3 Measuring diversity

There are a number of different diversity measures, most inspired by physics and biology. In Stirling (1998) you will find a comprehensive overview of different measures of diversity. They will be not repeated here. Basically, we want to focus on selected measures of importance for the formulation of the diversity measure applied in this investigation.

Our notion of measuring diversity is primarily inspired by biological diversity concepts. Nehring and Puppe (2002) propagated a multi-attribute approach in describing diversity. They isolated different attributes of species and pointed to dissimilarities in attributes. The smaller the probabilities of finding a specific attribute of a species, the higher its value for diversity.[6]

Nehring and Puppe (2002) formulated the following diversity function ($V(S)$):

$$V(S) = \lambda(\{A \subseteq X : A \cap S \neq \varnothing\}) = \sum_{A \subseteq X : A \cap S \neq \varnothing} \lambda_A \quad (1)$$

In Eq. 1, the diversity of a set S is determined by the frequency of attributes (A) possessed by the objects (species) in S ($S \subseteq X$; X is a finite universe of species). The function λ: $A \rightarrow \lambda_A$ indicates the attribute weighting function associated with V. λ_A can be understood as the relative importance of the corresponding attribute (A). The expression $\{A \subseteq X : \lambda_A \neq \varnothing\}$ is the set

[6]Solow et al. (1993) and Weitzman (1992, 1993) measured diversity based on genetic distances. They defined the value of a species for the diversity of a subsample S, according to the "genetic" distance to other species element of S. The genetic distances are measured, e.g. based on a taxonomic tree. Such a tree indicates the ancestors of a specific species and the time passed from its separation from the species. Thus the longer ago a species separated from another one, the greater is its "genetic" distance. This approach can be seen as a conceptual starting point for the Nehring and Puppe (2002) measure.

of attributes with nonzero weight that will be called the group of relevant attributes. Thus, each single species contributes to diversity according to the weight of all those attributes that are not possessed by any already existing object. This criterion is very strict, since it ignores how often certain attributes exist within a species. Certainly, the relative frequency of certain attributes may play an important role for the diversity, as we will see later when we focus on industries and firms and their different attributes.

Stirling (1998, 2004) introduced a measure of diversity considering variety, balance and disparity of "subsystems." Furthermore he integrated the different parts in a multi-criteria diversity index (M).

$$M = \sum\nolimits_{ij} d_{ij} p_i p_j \quad i \neq j \tag{2}$$

In Eq. 2, diversity is measured by the sum of weighted "distances" or dissimilarities between different objects (e.g. portfolios, technologies). Dissimilarities or distances are indicated through d_{ij} and the two weights are shown as p_i (relative number of characteristic i) and p_j (relative number of characteristic j). Intuitively one can see that $\sum_{ij}$ covers the variety component, d_{ij} symbolizes the disparity component, and p_i and p_j indicate the balance of the two characteristics. The latter is rather important in economic terms, since a high incidence of certain characteristics initiates competition and, as a consequence, promotes the evolution of the economic system. Stirling (2007) broadened this concept in permitting a systematic exploration of different possible weightings on this diversity measure.

For the purpose of the empirical test at hand on the impact of diversity on innovation performance, we refer to the two approaches. From Nehring and Puppe (2002) we learn that unique attributes rather than elements (whole entities) are important. From Stirling (1998) we learn that weights or frequencies according to structural conditions of elements (e.g. technologies) and dissimilarities between them are important as well. The two approaches have in common the measuring of diversity based on dissimilarities.

Following Nehring and Puppe (2002) our measure of diversity focuses on dissimilarities of firm attributes. We think that dissimilarities in firm characteristics, such as size, education level of the staff, export behavior and R&D intensity, have important implications for firm behavior and are important in describing the diversity of industries. In contrast to Nehring and Puppe (2002), we do not think that, in an economic context only, unique attributes are of value for diversity. It is more likely that dissimilarities between the just mentioned firm attributes may be responsible for routines and innovative behavior. Thus we apply a simple Euclidean distance measure in measuring diversity of an industry:

$$\mathrm{DIV}(S) = \sum_{j=1}^{m} \sqrt{\sum_{i=1}^{n} (X_i - Y_i)^2} \quad i \neq j \tag{3}$$

Following Eq. 3, the diversity (DIV) of industry (S) is the sum of the Euclidean distance of all possible pairs ($j = 1\dots\dots\dots m$) of firms ($\boldsymbol{X}, \boldsymbol{Y}$) based on their resource base ($i = 1\dots\dots 4$).[7] Thus we calculate the Euclidean distances between dissimilar firm attributes of all possible pairs of firms within an industry. Industries are defined on a two-digit level. This seems to be an adequate level of analysis for the purpose of this study for three reasons. First, the firm-panel has been drawn from the business census in terms of a disproportionately stratified random sample with respect to firm size and two-digit industry affiliation. Any different level of analysis would leave us with a completely accidental firm allocation to the respective, e.g., three-digit or four-digit level. Second, changing to a three digit-level would mean dropping more than half of the industries, since we would have less than 20 observations to calculate the diversity measure for the respective three-digit industry.[8] In choosing the SIC grouping of firms, one has to be aware that firms are affiliated with industries based on production and output similarity, and that industries are not very homogeneous within category levels (see Jacquemin and Berry 1979; Robins and Wiersema 1995). Furthermore, consumer characteristics, marketing similarities, distribution procedures, or innovation activities are not considered as SIC specific attributes (see Davis and Thomas 1993). Third, heterogeneity across firms seems to persist on a lower aggregation level as well. As Griliches and Mairesse (1997; cited in Dosi 2005) put it: "we ….. thought that one could reduce heterogeneity by going down from general mixtures as 'total manufacturing' to something more coherent, such as 'petroleum refining' or 'the manufacture of cement'. But something like Mandelbrot's fractal phenomenon seem to be at work here also: the observed variability-heterogeneity does not really decline as we cut our data finer and finer. There is a sense in which different bakeries are just as much different from each others as the steel industry is form the machinery industry."

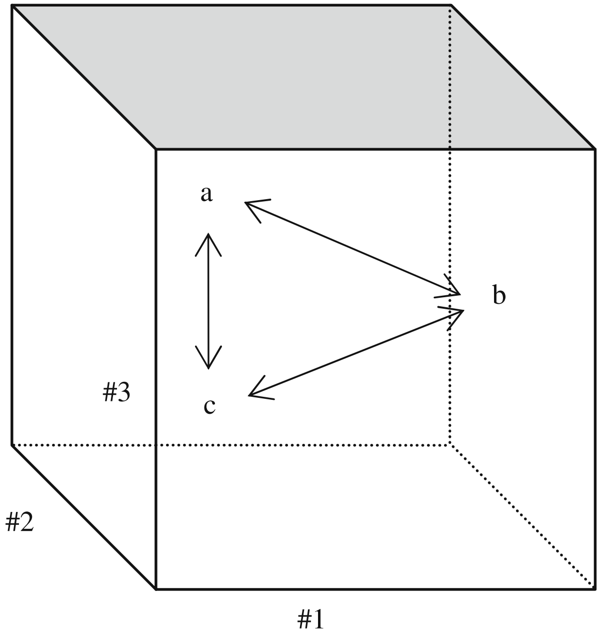
In order to imagine our distance measure graphically, we assume only three firm attributes (#1, #2, #3) and we have only three firms (a, b, c) in an industry. Thus one can image the diversity of this industry as shown in Fig. 1. The three firms are positioned according to their values for their three attributes, respectively. The greater the distances between the firms in the three dimensional space, the greater their dissimilarity and the greater industries' diversity.

In our empirical case, we measure diversity as to four different firm attributes, i.e. firm size, share of exports on total sales, share of R&D expenditures on total sales, and share of higher educated staff. These four attributes were chosen, since they have an influence on firm behavior in the market, on the way they "routinize" their work, and on the way they process information

[7] X_i = value in line i of firm vector $\boldsymbol{X}$; Y_i = value in line i of firm vector $\boldsymbol{Y}$.

[8] If we would change to a three digit level, we would have 191 different markets. In 118 markets we would have fewer than 20 observations. In 88 markets we would have fewer than ten firms and still, in 40 markets, there would be fewer than four observations.

Fig. 1 Diversity: stylised in a three dimensional space



in order to perceive relevant problems in the environment. In fact, Woerter (2007) showed that firm size, share of exports, R&D expenditures, and the share of higher educated staff significantly shape preferred ways of organizing R&D and innovation activities.[9] In order to measure the Euclidean distances, these four variables were standardized with mean 0 and standard deviation of 1.[10]

Table 1 shows some descriptive analysis of the diversity measure. It contains the degree of diversity for each industry in every single cross section and the aggregated degree of diversity by industry as an average of all three cross sections. It is worth noting that high-tech industries and modern service industries have a greater diversity than low-tech or traditional service industries. However, there are some exceptions. Metal working and food/beverages also show a rather great measure of diversity. Also, wholesale and retail sale are

[9]The importance of size for innovation performance on an industry level was also shown by Majumdar (1995) for the telecommunication sector. Tsai (2001) showed that even the size of business units impacts innovation behavior. The share of exports and R&D expenditures also impact the way firms organize their R&D. This was found in additional calculations based on the empirical models applied in Woerter (2007). The empirical data do not enable us to dig deeper into the driving forces for organizational routines, as investigated in Feldman (2000), or Becker et al. (2005).

[10]Standardization was conducted using SAS software according to the following formula: $x_i = \frac{S\times(x_i'-\bar{X})}{S_x} + M$; while x_i is the new standardized value, S is the chosen standard deviation value, M is the mean value, S_x is the variables standard deviation, x_i' is the observation's value, and $\overline{X}$ is the variables mean.

Table 1 Diversity measures for industries (1996, 1999, 2002)

	DIV(fa) × 100			
	t(1–3)	t1 (1996)	t2 (1999)	t3 (2002)
Manufacturing				
Food/beverage	152.96	152.41	147.31	157.50
Textile	145.01	148.91	139.57	145.96
Clothing/leather	96.54	97.17	108.67	76.36
Wood processing	123.34	133.32	110.72	119.77
Paper	112.77	106.11	101.50	123.98
Publishing	142.31	125.90	147.76	150.26
Petroleum/chemicals	180.66	171.63	180.31	186.21
Rubber/plastic product	147.29	148.81	135.73	153.93
Other non-metallic mineral products	126.07	125.23	124.46	128.27
Metal	111.67	119.68	96.91	114.34
Metalworking	196.73	199.93	184.39	202.07
Machinery	214.81	203.15	214.03	223.08
Electrical machinery	164.04	166.91	161.94	163.36
Electronic/instruments	204.17	198.32	197.01	213.07
Watches	138.84	134.81	148.09	129.84
Vehicles	125.74	133.92	101.45	132.63
Other manufacturing	135.33	134.82	116.77	148.95
Energy/water	112.54	n.a.	77.54	137.54
Construction	*172.82*	*165.36*	*181.92*	*170.92*
Services				
Wholesale	187.07	170.52	189.18	197.46
Retail trade	164.84	178.55	147.95	168.30
Hotels and restaurants	127.53	129.00	125.57	127.32
Transport/telecommunication	154.50	132.68	161.76	157.26
Banking/insurance	148.72	118.90	141.13	163.46
Real estate/renting	52.77	52.40	22.17	71.50
Computer services	183.09	198.37	170.96	173.85
Business services	202.49	200.96	198.08	207.93
Personal services	36.59	52.46	−28.39	46.16

Diversity (DIV(fa)) calculated according to formula (3) divided through the number of firms in the respective industry and multiplied the log of the result with 100.

very diverse. Following our assumption that diversity fosters innovation, it is shown that these industries have a greater potential for innovation than it is currently realized (of course, differences in the technological potential of those industries have to be considered).

4 Data

Our empirical investigation regarding the impact of diversity on the innovation performance of a firm is based on panel data covering three cross-sections, i.e. 1996, 1999 and 2002. The data were collected in the course of three postal surveys using a rather comprehensive questionnaire, which included questions on firm characteristics, the market environment, innovation activities, R&D activities and IPR (Intellectual Property Rights). The surveys were based on a (with respect to firm size and two-digit industry affiliation) disproportionately

Table 2 Number of observations (1996, 1999, 2002)

	Observations			
	t(1–3)	t1 (1996)	t2 (1999)	t3 (2002)
Manufacturing	*2,834*	*904*	*822*	*1,108*
Food/beverage	204	58	62	84
Textile	102	32	30	40
Clothing/leather	42	19	14	9
Wood processing	120	51	29	40
Paper	72	20	20	32
Publishing	186	55	56	75
Petroleum/chemicals	163	41	52	70
Rubber/plastic product	150	49	41	60
Other non-metallic mineral products	122	43	36	43
Metal	70	27	19	24
Metalworking	430	164	110	156
Machinery	448	124	136	188
Electrical machinery	127	40	39	48
Electronic/instruments	262	83	69	110
Watches	94	27	39	28
Vehicles	59	23	14	22
Other manufacturing	123	48	31	44
Energy/water	60	n.a.	25	35
Construction	*486*	*156*	*163*	*167*
Services	*1,625*	*477*	*485*	*663*
Wholesale	395	113	128	154
Retail trade	252	58	72	122
Hotels and restaurants	168	61	38	69
Transport/telecommunication	202	37	78	87
Banking/insurance	115	20	36	59
Real estate/renting	26	10	6	10
Computer services	106	43	26	37
Business services	319	116	94	109
Personal services	42	19	7	16
Total	4,945	1,537	1,470	1,938

Because of item non-response and some contradictions, non-plausible answers, 4,050 observations could be taken into consideration in our estimations (see Table 5). Since firms affiliated to the "energy/water industry" were not included in the survey 1999, we excluded them from the panel-estimations.

stratified random sample of firms with at least five employees covering all relevant industries of the manufacturing sector, the construction sector and the service sector, as well as firm size classes (on the whole, 27 industries and, within each industry, three industry-specific firm size classes with full coverage of the upper class of large firms).

Table 2 provides us with an overview of the different surveys. We received answers from 1,537 firms (response rate: 33.5%),[11] 1,470 firms (33.8%) and 1,938 firms (39.6%) for the years 1996, 1999, 2002, respectively. In sum, the

[11]This figure represents the response rate for the manufacturing sector. The response rate for the service sector and the construction sector amounts to 31.6%. The respective figures for 1999 and 2002 cover all three sectors.

firm panel covers 4,945 observations. Because of item non-response, and some conflicting, non-plausible answers, 4,050 observations could have been used for econometric estimations. Since our investigation only focuses on innovative firms, the panel estimation (see Table 5) is based on 2,539 observations.

5 Hypotheses and model specification

Following the modelling framework in section two and taking into account data restrictions, it is possible to specify the following model:

$$y_{it} = \beta_0 + \beta_1 \mathrm{HEDU} + \beta_2 \mathrm{CINT} + \beta_3 D + \beta_4 \mathrm{TPOT} + \beta_5 \mathrm{CONC} + \beta_6 \mathrm{IPC} + \beta_7 \mathrm{INPC} + \beta_8 \mathrm{DIV}\,(\mathrm{fa}) + \beta_9 \mathrm{SIZE} + \beta_{10} \mathrm{SEC} + \beta_{11} \mathrm{TDUM} + e_{it}$$

Our dependent variable (y_{it}) represents the innovation performance of a firm and is measured through the share of innovative products on total sales (see Table 3). i represents the number of firms and t indicates the years 1996, 1999 or 2002.

The vector of independent variables (see Table 4) consists of variables representing the resource base of a firm. HEDU (share of employees with higher education) represents the human capital of a firm, assumed to have a positive impact on innovation performance. Also, the second variable representing the resource base of a firm, the physical capital intensity (CINT), is likely to show a significant positive impact on the dependent variable.

Demand pull effects are indicated by the variable D, measured through the medium-term expected change of demand as is perceived by the respondents to our questionnaires. It is assumed that demand pull effects have a positive impact on the innovation performance of the firm. The same is true for TPOT. This variable proxies the general technological potential relevant to the firm's innovation activity and represents technology push effects. Firms with greater technological potentials should be more innovative than others.

The competitive environment is assumed to have a significant impact on innovation performance as well. We apply two different measures for competition. The first is a concentration measure, based on the number of principal competitors in the world (product) market. There are five dummy variables, i.e. fewer than five competitors, between five and ten competitors, between 11 and 15 competitors, between 16 and 50 competitors, and more than 50 competitors (reference). It is assumed that more competitors intensify competition and thus promote innovative behavior. There are two further variables that characterize the competitive environment as well. IPC informs

Table 3 Dependent variable

Dependent variable	Description
INPD	Logarithm of innovative products on total sales for the years 1996, 1999, 2002

Table 4 Determinants of firms' innovation performance—Independent variables

Independent variables	Description	Expected sign
Resource base		
HEDU (human capital)	Logarithm of the share of employees with tertiary-level vocational education 2005 (universities, universities of applied sciences, other business and technical schools at tertiary level)	+
CINT (physical capital)	Logarithm of the share of value added and personnel costs on total sales	+
Demand (pull)		
D	Medium-term expected change in demand (on a five point Likert-scale; 1 strong decline, 5 strong increase)	+
Technological opportunities (push)		
TPOT	General technological potential, i.e. scientific and technological knowledge relevant to the firm's innovation activity (on a five point Likert-scale; 1 very low, 5 very high technological potential)	+
Competitive environment		
CONC	Concentration measure based on the number of principal competitors in the world (product) market (dummy variables: CONC5 = less than 5; CONC5–10 = 5 to 10; CONC11–15 = 11 to 15; CONC16–50 = 16 to 50; CONC50 = more than 50 is the reference group)	+
IPC	Intensity of price competition in the product market	+
INPC	Intensity of non-price competition in the product market	+
Diversity (industry-level)		
DIV	Logarithm of the sum of Euclidean distances of differences in the resource base of firms affiliated to the same industry, i.e. differences in human capital, knowledge capital, international market experiences and firm size. Human capital is measured through share of employees with tertiary-level vocational education. Knowledge capital is measured through share of R&D expenditures on total sales. International experiences are indicated through share of exports on total sales and number of employees (in full-time equivalents) is a proxy for firm size. In order to calculate the Euclidean distances all applied variables have been standardised with mean 0 and standard deviation of 1.	+

Table 4 (continued)

Independent variables	Description	Expected sign
DIV(fa)	We divide the sum of Euclidean distances through the number of firms affiliated to an industry and take the logarithm. Thus the average contribution of a firm to industries' diversity is indicated.	+
Control variables		
SIZE (G1 to G7)	Seven size dummy variables (SIZE) based on number of employees (full-time equivalent); G1 (<20), G2 (20–<50), G3 (50–<100), G4 (100–<200), G5 (200–<500), G6 (500–<1000), G7 (1000+). Reference size dummy = G1	+
TDUM (DUM96, DUM99, DUM02)	Three time-dummy variables (TDUM) for the cross-sections 1996, 1999 and 2002 respectively (DUM96 is the reference)	-
SEC (HTCH, LTCH, CONSTR, MSER, TSER)	Five sector dummy variables (SEC) based on the sector affiliation of the firm; HTCH (high-tech firms; petroleum/chemicals, plastics/rubber, machinery electrical machinery, electronic/instruments, vehicles), LTCH (low-tech firms; food/beverage, textile, clothing/leather, wood processing, paper, publishing glass/stone/clay, metal, metal working, watches, other manufacturing, energy/water); CONSTR (construction sector), MSER (modern services; banking/insurance, computer services, business services) TSER (traditional services; wholesale, retail trade, hotels and restaurants, transport/telecommunication, real estate/renting, personnel services). Reference sector = CONSTR	+

us about the intensity of price competition in the product market. INPC reveals the intensity of non-price competition in the product market, measured through the importance of several non-price competition dimensions, e.g. quality based competition, customization, range of goods, technology advance, service, design. Respondents were asked to assess the importance of such items on a five point Likert-scale (1 means less important for competition, 5 means very important for competition). In order to build INPC, we summed up the scores and divided it by the number of non-price competition dimensions. For both IPC and INPC, a positive impact on the innovation performance of a firm is expected.

Diversity is measured according to expression (3), focusing on the resource base of a firm, i.e. human capital, knowledge capital, international market experiences and firm size. Dissimilarities in these factors are responsible for different firm routines and different perceptions of the economic environment. In general, it is hypothesized that firms embedded in a more diverse industry have a better innovation performance than firms embedded in less diverse industry environments. There are two variables for diversity of an industry. DIV measures the sum of Euclidean distances (logarithm) and DIV(fa) shows the average contribution of a firm to industry diversity by dividing the sum of Euclidean distances by the number of firms affiliated with an industry. In the paper at hand, we only present the estimation with DIV(fa). However, DIV also has a positive impact on the dependent variable.

There are a number of control variables in the estimation. We built seven size dummies (SIZE: G1 to G7), whereas firms with fewer than 20 employees (G1) are the reference group. Furthermore, there are five sector dummies (SEC) referring to firms affiliated with the high-tech manufacturing sector (HTCH), to firms affiliated to the low-tech manufacturing sector (LTCH), the construction sector (CONSTR), the modern service sector (MDL) and the traditional service sector (TDL). Firms in the construction sector act as a reference in the estimation. Three time-dummies (TDUM) refer to the cross-sections 1996 (DUM96), 1999 (DUM99) and 2002 (DUM02), respectively. DUM96 is the reference.

6 Estimation results and the impact of diversity on innovation performance

Table 5 shows the results of our panel estimation. The random effect tobit procedure was found to be an efficient estimator for several reasons. First, our dependent variable (INPD) is very right skewed. Second, there is a possibility of a selectivity bias, since not all of the responding panel-firms have innovations. A Heckman procedure (see Heckman 1976) was applied to detect the possible bias. In fact, no selection bias was detected. The chi-square test on the correlation of the two error-components (for selection specification and for intensity specification) was not significant (Wald test of independent equations [$\rho = 0$]: $chi2(1) = 1.27$; prob. $>$ $chi2 = 0.2602$). Third, heteroskedasticity and autocorrelation are two more possible sources of inefficient panel estimation.

Table 5 Estimation results

INPD	Coef.	Std. err.	z	$P > \|z\|$	95% conf. interval	
HEDU	0.0971	0.0262	3.71	0.000	0.0458	0.1484
CINT	0.0504	0.0288	1.75	0.081	−0.0061	0.1069
G2	0.0595	0.0700	0.85	0.395	−0.0777	0.1968
G3	−0.0998	0.0725	−1.38	0.169	−0.2420	0.0424
G4	−0.0888	0.0737	−1.21	0.228	−0.2332	0.0555
G5	−0.0533	0.0774	−0.69	0.491	−0.2050	0.0984
G6	−0.1250	0.1079	−1.16	0.247	−0.3365	0.0865
G7	−0.1638	0.1415	−1.16	0.247	−0.4412	0.1135
DIV(fa)	0.3485	0.0747	4.67	0.000	0.2021	0.4948
DUM99	−0.2439	0.0500	−4.88	0.000	−0.3420	−0.1459
DUM02	−0.1727	0.0469	−3.68	0.000	−0.2646	−0.0808
INPC	0.0844	0.0229	3.68	0.000	0.0394	0.1294
IPC	−0.0056	0.0210	−0.27	0.790	−0.0468	0.0356
CONC5	0.0241	0.0683	0.35	0.725	−0.1098	0.1580
CONC5–10	0.0709	0.0653	1.09	0.278	−0.0572	0.1990
CONC11–15	0.1866	0.0743	2.51	0.012	0.0411	0.3321
CONC16–50	0.1000	0.0736	1.36	0.174	−0.0442	0.2443
D	0.0910	0.0227	4.01	0.000	0.0465	0.1355
TPOT	0.1344	0.0194	6.94	0.000	0.0964	0.1723
HTCH	1.0366	0.1042	9.95	0.000	0.8324	1.2408
LTCH	0.8572	0.1026	8.35	0.000	0.6561	1.0583
MDL	0.4108	0.1174	3.50	0.000	0.1806	0.6409
TDL	0.4443	0.1089	4.08	0.000	0.2307	0.6578
_cons	−0.1139	0.2295	−0.50	0.620	−0.5637	0.3359
/sigma_u	0.6505	0.0398	16.34	0.000	0.5725	0.7285
/sigma_e	0.8110	0.0270	30.01	0.000	0.7580	0.8639
rho	0.3915	0.0425			0.3113	0.4766

Random-effects tobit regression: Number of observations = 2,539, Number of groups = 1,933. Obs. per group: min = 1, avg = 1.3, max = 3. Log likelihood = −3,640.0093. Wald chi2(23) = 460.73, Prob > chi2 = 0.0000. Observation summary: left-censored observations = 185, uncensored observations = 2,354, right-censored observations = 0

As to heteroskedasticity, we carried out a likelihood-ratio test comparing GLS (General least squares) estimates under the assumption of heteroskedasticity with GLS estimates under the assumption of homoskedasticity.[12] The likelihood-ratio test assumes that the homoskedastic estimates are nested in the heteroskedastic ones. The result showed no significant heteroskedastic bias (prob. > chi2 = 0.0014). In order to investigate a possible autocorrelation bias, the Wooldridge test for autocorrelation in panel data was applied (see Wooldridge 2002, pp. 282–283) using STATA software; no significant serial correlation was detected (H0: no first-order autocorrelation, prob. > $F =$ 0.2135).[13] Fourth, the results are also not affected by multicollinearity (see correlations in Table 6 in Appendix).

[12]In order to carry out this calculation, we used the STATA software.

[13]The Heckman estimation, the test for heteroscedasticity and autocorrelation are not presented in the paper.

We tested the main hypotheses put forward by the innovation literature on the most important drivers for innovation activities in firms. Technology push as well as the demand pull effects are significantly positively correlated with the innovation intensity of a firm. Both variables, *D* and TPOT for the demand pull and technology push effect, respectively, show a significant positive sign. These results for Switzerland (including manufacturing, construction and services) are in line with the investigations on the manufacturing sector in France (see Crépon et al. 1998) in The Netherlands (see Brouwer and Kleinknecht 1996), and in Ireland (see Mohnen and Dagenais 2001) as to the demand pull effect. Also, Raymond et al. (2004) saw again for The Netherlands a significant positive impact of demand pull effects on the innovation performance of manufacturing firms. However, the variable for technology push did not show any effect in this analysis.

As expected, the resource base of a firm is very important for innovation activities. We see that the variables for human capital (HEDU) as well as physical capital (CINT) have a significant positive impact on the share of innovative products on total sales (INPD). In addition, the competitive environment has an impact on the innovation performance of firms. The intensity of non-price competition fosters innovations, while price competition does not show any significant impact. The number of principal competitors has a rather weak impact on the innovation performance. Only one dummy (CONC11–15) shows a significant impact compared to CONC50 (as reference). This indicates that more oligopolistic-like market circumstances, where the number of competitors is manageable, are more conducive for innovation than polypolistic-like market circumstances (more than 50 principal competitors). However, variables representing fewer than five competitors (CONC5) or between five and ten competitors (CONC5–10) do not differ significantly from the reference variable, implicating that there is no clear tendency towards a positive impact of fewer market participants on innovation activities.

The variable for diversity (DIV(fa)) shows a significant positive impact on the innovation intensity of a firm. Thus, the hypotheses is supported that firms in more diverse industries show a relatively better innovation performance than firms in less diverse ones. Thus, we can empirically confirm the findings of Chiaromonte and Dosi (1993), Silverberg et al. (1988) and Llerena and Oltra (2002) that more diverse economic behavior or asymmetric firm structures indicate a better innovation or technological performance. Following this, it could be at least to some extent misleading to analyze drivers of innovation based on representative homogeneous agents. Rather than homogeneity it is their diversity that drives innovation and technology. In addition to this more conceptual implication, there are some policy-making as well.

One can ask how diversity in industries can be promoted. Many innovations stem from new, very often small entrant firms. They discover economic niches and successfully fill them or they may serve larger, incumbent firms with specialized products that enable them to be innovative as well. Contestable markets and diversity may positively interact in order to increase market flexibility to react upon new challenges and make innovations more likely. This way, diversity is a possible indicator of market contestability.

Innovation policy measures should not only focus on certain types of firms, but should also identify differences in approaches or subjects. This way innovation policy remains neutral as at to firm heterogeneity in industries, or even supports it. Diversity may be promoted if innovation policy causes some behavioral additionality, i.e. a firm carries out a research project that would have been dropped without public support. However, such investigations must be left for future research and cannot be done within the framework of the study at hand.

Causality between the measure for diversity and the dependent variable could be a further interesting topic. It was not possible to control for simultaneity between these two variables, since we lack a theory of what determines the diversity of industries and thus only a very ad-hoc specification of diversity would have been possible. We abandoned this line of research here. The quest for determinants for diversity is left for future research. However, it was possible to lag the diversity variable (estimation not shown in this paper) and it was found that the significant positive relation with the dependent variable remained stable, indicating that causality runs from diversity to innovation (lag three years). Certainly the contrary is also possible, although with perhaps different lag structures.

Firm size does not play any significant role. Our size dummies do not differ significantly from the reference size (fewer than 20 employees). This result is in line with the investigations from Crépon et al. (1998) and Mohnen and Dagenais (2001). Further control variables for sector affiliation (HTCH, LTCH, MDL, TDL) and cross-sections (DUM99, DUM02), respectively, are significant. Firms affiliated with the construction sector are significantly less innovative than firms affiliated with the high-tech, low-tech, modern services or traditional service sector. The cross-section dummies mirror the overall innovation performance of Swiss firms. The time dummies for the years 1999 and 2002, respectively, show a significant negative sign (reference DUM96). This is not surprising, taking into account the rather poor overall economic development and its negative impact on the innovation performance in Switzerland during the second half of the nineties.

7 Summary and conclusions

Diversity is seen as the main driving force for evolution. In order to test empirically the impact of diversity on the innovation performance of a firm, we mainly refer to the work of Nelson and Winter (1982) stating that economic evolution is driven by agents confronted with bounded rationality and uncertain circumstances. Furthermore, Nelson (1995) emphasized the importance of routines to reduce complexity. Acknowledging that routines are determined by the resource base of a firm, we develop a diversity measure that measures the differences in the resource base of firms and thus enables us to test whether this kind of diversity (diversity in resources and in working routines) has a positive impact on innovation intensity in addition to more traditional important drivers of innovation, e.g. technology-push, demand-pull, and firm size.

Based on a comprehensive panel data covering three cross-sections (1996, 1999, 2002), it was found that diversity has a significant positive impact on the innovation performance (intensity) of a firm. Thus we can empirically confirm the more theoretical investigations on diversity and innovation or technological change (see Silverberg et al. 1988; Chiaromonte and Dosi 1993 or Llerena and Oltra 2002), and it becomes empirically obvious that differences in economic agents (firms) promote innovative behavior.

This result has several implications for economic innovation research and policy making. It put some doubt on the usefulness of “representative agents” in order to model innovative behavior. We saw that, rather than their homogeneity it is their diversity that promotes innovation.

Industry diversity may be also a challenge for national competition authorities. A competitive environment that is characterized by firm diversity promotes innovations and, following Jacobs (1969) conclusions, facilitates the entry of new firms that may be specialized in some particular, new, product niches. Following the contestable market theory, markets should be open for new qualified entry that in turn promote diversity of industries, and vice versa.

Industry diversity may be also a challenge for innovation policy. It could contribute to an increase or a decrease in industry diversity and thus may multiply its likely positive effect on innovation performance by not only promoting innovative behavior directly, but by contributing to a diverse research environment. Thus, policy measures should be neutral as to firm heterogeneity in industries or even promote it. Diversity would be promoted if innovation policy causes some behavioral additionality, i.e. a firm addresses an urgent problem through research projects that would have been not been considered (lacking resources) without public support.

Certainly one could argue that there can be too much diversity at the cost of efficiency. Thus, finding a balance between efficiency and effectivity, as was questioned by March (1994), could be a future topic for investigation. Also, to investigate empirically diversity and its relation to productivity or its meaning for technological diffusion as well as a more detailed investigation of the “causality” question must be left for future empirical research.

Acknowledgements I would like to thank N. Sydow for programming SAS macros in order to apply the measure of diversity. Many thanks also to N. Lazaric and Th. Brenner (discussants at the Druid Conference 2007) and S. Arvanitis, A. Mueller, and the participants of the KOF research seminar for their valuable comments on the paper.

Appendix

Table 6

Table 6 Correlations between determinants

	HEDU	CINT	G2	G3	G4	G5	G6	G7	DIV(fa)	DUM99	DUM02	INPC	IPC	CONC5	CONC5–10	CONC11–15	CONC16–50	D	TPOT	HTCH	LTCH	MDL	TDL
HEDU	1.000																						
	4,853																						
CINT	−0.025	1.000																					
	0.081																						
	4,853	4,945																					
G2	−0.020	0.035	1.000																				
	0.163	0.014																					
	4,853	4,945	4,945																				
G3	−0.024	0.006	−0.251	1.000																			
	0.101	0.693	0.000																				
	4,853	4,945	4,945	4,945																			
G4	0.041	−0.041	−0.246	−0.206	1.000																		
	0.004	0.004	0.000	0.000																			
	4,853	4,945	4,945	4,945	4,945																		
G5	0.053	−0.008	−0.203	−0.169	−0.166	1.000																	
	0.000	0.573	0.000	0.000	0.000																		
	4,853	4,945	4,945	4,945	4,945	4,945																	
G6	0.058	−0.023	−0.115	−0.096	−0.094	−0.078	1.000																
	0.000	0.110	0.000	0.000	0.000	0.000																	
	4,853	4,945	4,945	4,945	4,945	4,945	4,945																
G7	0.031	−0.017	−0.089	−0.075	−0.073	−0.060	−0.034	1.000															
	0.032	0.222	0.000	0.000	0.000	0.000	0.016																
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945															
DIV(fa)	0.216	−0.083	0.001	−0.018	0.015	−0.016	−0.002	−0.005	1.000														
	0.000	0.000	0.957	0.219	0.309	0.266	0.874	0.751															
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945														
DUM99	0.015	−0.051	−0.014	−0.003	0.045	0.014	0.007	0.022	−0.062	1.000													
	0.312	0.000	0.330	0.821	0.002	0.333	0.624	0.119	0.000														
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945													
DUM02	0.024	−0.024	0.013	0.016	0.002	−0.013	−0.001	−0.042	0.120	−0.522	1.000												
	0.089	0.094	0.375	0.277	0.881	0.362	0.940	0.003	0.000	0.000													
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945												
INPC	0.038	0.036	−0.014	−0.009	−0.011	0.003	0.034	0.061	0.046	0.047	−0.114	1.000											

	0.010	0.014	0.350	0.556	0.441	0.813	0.019	0.000	0.002	0.001	0.000												
	4,636	4,723	4,723	4,723	4,723	4,723	4,723	4,723	4,723	4,723	4,723	4,723											
IPC	0.005	−0.047	−0.004	0.019	0.067	0.030	0.033	0.040	0.010	−0.050	−0.029	0.087	1.000										
	0.737	0.001	0.779	0.193	0.000	0.040	0.023	0.006	0.500	0.001	0.046	0.000											
	4,704	4,792	4,792	4,792	4,792	4,792	4,792	4,792	4,792	4,792	4,792	4,705	4,792										
CONC5	0.035	−0.023	−0.034	−0.018	0.003	0.037	0.036	0.019	0.014	−0.008	0.052	−0.064	−0.162	1.000									
	0.017	0.109	0.020	0.222	0.843	0.011	0.012	0.197	0.339	0.594	0.000	0.000	0.000										
	4,752	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,656	4,721	4,835									
CONC5-10	0.039	0.002	−0.021	0.020	0.047	0.021	0.038	0.019	0.050	0.029	0.010	0.028	0.028	−0.330	1.000								
	0.008	0.913	0.149	0.164	0.001	0.141	0.009	0.193	0.001	0.045	0.491	0.053	0.052	0.000									
	4,752	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,656	4,721	4,835	4,835								
CONC11-15	−0.017	−0.012	0.009	0.023	0.014	0.008	−0.020	0.007	0.022	−0.006	0.010	0.012	0.038	−0.216	−0.237	1.000							
	0.250	0.425	0.526	0.112	0.326	0.592	0.158	0.611	0.123	0.655	0.505	0.396	0.009	0.000	0.000								
	4,752	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,656	4,721	4,835	4,835	4,835							
CONC16-50	−0.011	−0.025	0.025	−0.005	0.012	−0.004	−0.013	−0.002	−0.018	−0.019	−0.011	−0.035	0.065	−0.228	−0.252	−0.165	1.000						
	0.456	0.077	0.078	0.727	0.424	0.786	0.381	0.867	0.220	0.186	0.445	0.016	0.000	0.000	0.000	0.000							
	4,752	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,835	4,656	4,721	4,835	4,835	4,835	4,835						
D	0.110	0.028	−0.039	0.014	0.022	0.036	0.055	0.070	0.074	0.222	−0.034	0.076	−0.091	0.091	0.054	−0.020	−0.044	1.000					
	0.000	0.054	0.007	0.332	0.131	0.013	0.000	0.000	0.000	0.000	0.018	0.000	0.000	0.000	0.000	0.172	0.003						
	4,686	4,773	4,773	4,773	4,773	4,773	4,773	4,773	4,773	4,773	4,773	4,598	4,662	4,698	4,698	4,698	4,698	4,773					
TPOT	0.194	−0.010	−0.066	−0.005	0.040	0.060	0.053	0.075	0.146	0.000	−0.039	0.166	0.042	0.022	0.066	−0.003	−0.022	0.180	1.000				
	0.000	0.503	0.000	0.753	0.007	0.000	0.000	0.000	0.000	0.991	0.008	0.000	0.005	0.147	0.000	0.851	0.147	0.000					
	4,473	4,554	4,554	4,554	4,554	4,554	4,554	4,554	4,554	4,554	4,554	4,384	4,436	4,469	4,469	4,469	4,469	4,420	4,554				
HTCH	0.180	−0.022	−0.045	0.001	0.065	0.023	0.057	0.029	0.360	−0.009	0.023	0.083	0.029	0.048	0.104	0.042	−0.054	0.141	0.231	1.000			
	0.000	0.128	0.002	0.967	0.000	0.114	0.000	0.043	0.000	0.543	0.101	0.000	0.046	0.001	0.000	0.004	0.000	0.000	0.000				
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,723	4,792	4,835	4,835	4,835	4,835	4,773	4,554	4,945			
LTCH	−0.149	0.049	−0.002	0.033	0.028	0.023	−0.027	−0.054	−0.355	−0.011	−0.024	−0.031	0.035	−0.013	0.030	0.009	0.002	−0.086	−0.072	−0.398	1.000		
	0.000	0.001	0.889	0.019	0.047	0.104	0.063	0.000	0.000	0.424	0.096	0.031	0.014	0.360	0.040	0.528	0.867	0.000	0.000	0.000			
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,723	4,792	4,835	4,835	4,835	4,835	4,773	4,554	4,945	4,945		
MDL	0.215	0.073	−0.010	−0.049	−0.066	−0.038	0.007	0.033	0.196	−0.006	−0.009	0.057	−0.086	−0.007	−0.021	−0.035	−0.026	0.070	0.090	−0.199	−0.245	1.000	
	0.000	0.000	0.475	0.001	0.000	0.008	0.604	0.021	0.000	0.652	0.536	0.000	0.000	0.620	0.149	0.015	0.077	0.000	0.000	0.000	0.000		
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,723	4,792	4,835	4,835	4,835	4,835	4,773	4,554	4,945	4,945	4,945	
TDL	−0.180	−0.031	0.056	−0.003	−0.074	−0.038	−0.014	0.031	−0.153	0.007	0.033	0.009	−0.066	0.049	−0.084	−0.036	−0.010	−0.010	−0.147	−0.302	−0.371	−0.186	1.000
	0.000	0.031	0.000	0.853	0.000	0.007	0.335	0.032	0.000	0.627	0.021	0.519	0.000	0.001	0.000	0.013	0.506	0.509	0.000	0.000	0.000	0.000	
	4,853	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,945	4,723	4,792	4,835	4,835	4,835	4,835	4,773	4,554	4,945	4,945	4,945	4,945

References

Arvanitis S, Hollenstein H (1996) Industrial innovation in Switzerland: a model-based analysis with survey data. In: Kleinknecht A (ed) Determinants of innovation, the message from new indicators. Macmillan, London, pp 13–62

Becker MC, Lazaric N, Nelson RR, Winter SG (2005) Applying organizational routines in understanding organizational change. Ind Corp Change 14(5):775–791. doi:10.1093/icc/dth071

Brouwer E, Kleinknecht A (1996) Determinants of innovation: a micro econometric analysis of three alternative innovative output indicators. In: Kleinknecht A (ed) Determinants of innovation, the message from new indicators. Macmillan, London, pp 99–124

Chiaromonte F, Dosi G (1993) The micro foundations of competitiveness and their macroeconomic implications. In: Foray D, Freeman Ch (eds) Technology and the wealth of nations. Pinter, London, pp 107–134

Cohen WM (1995) Empirical studies of innovative activity and performance. In: Stoneman P (ed) Handbook of the economics of innovation and technological change. Blackwell, Oxford

Cohen WM, Levin RC (1989) Empirical studies of innovation of market structure. In: Schmalensee R, Willig R (eds) Handbook of industrial organization. North-Holland, Amsterdam

Crépon B, Duguet E, Mairesse J (1998) Research and development, innovation and productivity: an econometric analysis at the firm level. Econ Innov New Technol 7(2):115–158

Davis R, Thomas LG (1993) Direct estimation of synergy: a new approach to the diversity–performance debate. Manag Sci 39(11):1334–1346

Dosi G (1988) Sources, procedures, and microeconomic effects of innovation. J Econ Lit 26:1120–1171 (September)

Dosi G (2005) Statistical regularities in the evolution of industries. A Guide through some evidence and challenges for the theory. LEM working-paper series 2005/17, Pisa

Feldman MS (2000) Organizational routines as a source of continuous change. Organ Science 11(6):611–629 (November–December)

Feldman MP, Audretsch DB (1999) Innovation in cities: science-based diversity, specialisation and localized competition. Eur Econ Rev 43:409–429

Glaeser E, Kallal H, Scheinkam J, Shleifer A (1992) Growth in cities. J Polit Econ 100:1126–1152

Greunz L (2004) Industrial structure and innovation—evidence from European regions. J Evol Econ 14:563–592. doi:10.1007/s00191-004-0234-8

Griliches Z, Mairesse J (1997) Production function: the search for identification. In: Strøm S (ed) econometrics and econmic theory in the Twentieth Century: the Ragner Frisch Centennial Symposium. Cambridge University Press, Cambridge, MA

Heckman JJ (1976) The common structure of statistical models of truncation, sample selection, and limited dependent variables and a simple estimator for such models. Ann Econ Soc Meas 5:475–492

Henderson V, Kuncoro A, Turner M (1995) Industrial development in cities. J Polit Econ 103(5):1067–1090

Holland JH, Holyoak KJ, Nisbett RR, Thagard PE (1986) Induction—processes of inference, learning, and discovery. MIT, Boston, MA

Jacobs J (1969) The economy of cities. Random House, New York

Jacquemin AP, Berry CH (1979) Entropy measure of diversification and corporate growth. J Ind Econ 27(4):359–369

Janz N, Lööf H, Peters B (2003) Firm level innovation and productivity—is there a common story across countries? Probl Perspect Manag 2:1–22

Lazaric N, Denis B (2005) Routinization and memorization of tasks in a workshop: the case of the introduction of ISO norms. Ind Corp Change 14(5):873–896

Llerena P, Oltra V (2002) Diversity of innovative strategy as a source of technological performance. Struct Change Econ Growth 13:179–201

Mairesse J, Mohnen P (2001) To be or not to be innovative: an exercise in measurement. MERIT-Infonomics Research Memorandum series Nr. 2001-039, MERIT, Maastricht

Majumdar SK (1995) The determinants of investment in new technology: an examination of alternative hypotheses. Technol Forecast Soc Change 50:235–247

Mansfield E (1968) The economics of technical change. Norton, New York

March JG (1994) Three lectures on efficiency and adaptiveness in organization. First Goran and Louise Ehrnrooth Lectures, Helsinki
Metcalfe JS, Miles I (1994) Standards, selection and variety: an evolutionary approach. Inform Econ Policy 6:243–268
Mohnen P, Dagenais M (2001) Towards an innovation intensity index. The case of CIS 1 in Denmark and Ireland. In: Kleinknecht A, Mohnen P (eds) Innovation and Firm Performance. Econometric Explorations of Survey Data. Palgrave, London
Nehring K, Puppe C (2002) A theory of diversity. Econometrica 70(3):1155–1198
Nelson RR (1959) The simple economics of basic scientific research. J Polit Econ 67:297–306
Nelson RR (1995) Recent evolutionary theorizing about economic change. J Econ Lit 33:48–90 (March)
Nelson RR (2006) Commentary on Sidney Winter's "Toward a neo-Schumpeterian theory of the firm". Ind Corp Change 15(1):145–149
Nelson RR, Winter SG (1982) An evolutionary theory of economic change. Belknap of Harvard University Press, Cambridge, MA
Nguyen P, Saviotti PP, Trommetter M, Bourgeois B (2005) Variety and the evolution of refinery processing. Ind Corp Change 14(3):469–500
Pentland BT, Feldman MS (2005) Organizational routines as a unit of analysis. Ind Corp Change 14(5):793–815
Phillips A (1966) Patents, competition, and technical progress. Am Econ Rev 56:301–310
Raymond W, Mohnen P, Palm F, Van der Loeff SS (2004) An empirically-based taxonomy of Dutch manufacturing: innovation policy implications. MERIT-Infonomics Research Memorandum series 2004-011, MERIT, Maastricht
Robins J, Wiersema MF (1995) A resource-based approach to the multibusiness firm: empirical analysis of portfolio interrelationships and corporate financial performance. Strateg Manage J 16(4):277–299
Rosenberg N (1976) Perspectives on technology. Cambridge University Press, Cambridge, MA
Saviotti PP (1996) Technological evolution, variety and the economy. Edward Elgar, Cheltenham
Saviotti PP, Mani GS (1995) Competition, variety and technological evolution: a replicator dynamics model. J Evol Econ 5:369–392
Schmookler J (1966) Invention and growth, Schumpeterian perspectives. MIT, Cambridge, Mass
Schumpeter AJ (1912) Theorie der wirtschaftlichen entwicklung. Duncker und Humblot, Leipzig
Schumpeter AJ (1975) Capitalism, socialism and democracy. Harper Perennial, New York
Silverberg G, Dosi G, Orsenigo L (1988) Innovation, diversity and diffusion: a self-organisation model. Econ J 98:1032–1054 (December)
Simon HA (1956) Rational choice and the structure of the environment. In: Egidi M, Marris R (eds) Economics, bounded rationality and the cognitive revolution, Herbert Simon. Edward Elgar, Aldershot, Brookfield (rev. 1992)
Simon HA (1981) Entscheidungsverhalten in organisationen. Verlag Moderne Industrie, Munich
Solow A, Polasky St, Broadus J (1993) On the measurement of biological diversity. J Environ Econ Manage 24:60–68
Stirling A (1998) On the economics and analysis of diversity. SPRU electronic working paper series, paper no. 28, October
Stirling A (2004) Diverse design: fostering technological diversity in innovation for sustainability. Paper submitted to Colloquium DEA, Durham Business School and Cranfield School of Management on: the role of diversity in social systems and its relation to innovation, Bologna, 12–13 July
Stirling A (2007) A general framework for analysing diversity in science, technology and society. J R Soc Interface 4:707–719
Tsai W (2001) Knowledge transfer in intraorganizational networks: effects of network position and absorptive capacity on business unit innovation and performance. Acad Manage J 44(5): 996–1004
Utterback JM (1996) Mastering the dynamics of innovation. Harvard Business School, Boston, MA
Weitzman ML (1992) On diversity. Q J Econ 107(2):363–405 (May)

Weitzman ML (1993) What to preserve? An application of diversity theory to crane conservation. Q J Econ 108(1):157–183 (February)

Wernerfelt B (1984) A resource-based view of the firm. Strateg Manage J 5:171–180

Winter SG (2006) Toward a neo-Schumpeterian theory of the firm. Ind Corp Change 15(1): 125–141

Woerter M (2007) Driving forces for research and development strategies. KOF working paper no. 184, Zurich. www.kof.ethz.ch

Wooldridge JM (2002) Econometric analysis of cross section and panel data. MIT, Cambridge, MA