Imitation versus innovation

What makes the difference?

KOF

KOF Working Papers

Imitation versus Innovation: What Makes the Difference?

Spyros Arvanitis and Florian Seliger

No. 367
August 2014

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

KOF

KOF Swiss Economic Institute
ETH Zurich
LEE G 116
Leonhardstrasse 21
8092 Zurich
Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Imitation versus Innovation: What Makes the Difference?

Spyros Arvanitis
ETH Zurich, KOF Swiss Economic Institute
8092 Zurich, Switzerland
Phone: +41 44 632 51 68
E-mail: arvanitis@kof.ethz.ch

Florian Seliger
ETH Zurich, KOF Swiss Economic Institute
8092 Zurich, Switzerland
Phone: +41 44 632 37 17
E-mail: seliger@kof.ethz.ch

August 2014

Abstract

The main objective of this empirical paper is to identify characteristics of imitation and innovation and shed light on possible differences between these two kinds of innovative activity. Thus, it tries to answer the following questions: (a) what are the determinants of imitative performance compared to determinants of innovative performance and (b) what are the determinants of switching from imitative to innovative behavior compared to imitators and innovators showing persistence over time. The study is based on Swiss firm data. In sum, our findings indicate that imitating firms are significantly more 'extroverted' than innovating firms because their activities are much more related to external R&D activities and cooperation and medium-educated personnel. Innovating firms do not rely to the same extent on the exploration of external knowledge. Their rather 'introverted' behavior seems be more related with intense exploitation of internal resources. Further, the profiles of different types of innovating firms show that an innovation performance hierarchy exists ranking from occasional innovators through switchers to persistently innovating firms.

Key words: innovation; imitation

JEL classification: O31

1. Introduction

As is currently done in the Innovation Surveys of the European Union (CIS), the distinction between ’imitation’ and ‘innovation’ can be attained through the differentiation of product innovations into ‘new-to-the-market’ innovations and ‘new-to-the-firm’ innovations, where ‘new-to-the-firm’ innovations are interpreted as resulting from imitating behavior (Kleinknecht et al. 2002). At the theoretical level, this distinction has been often substantiated through the analysis of the role of competition. Aghion et al. (2001, 2005) consider the relationship between competition and innovation where imitation is necessary to escape competition. Laggard firms first need to catch up with the technological leader before racing for the next innovation. These authors find that in industries where firms are closer to the technological frontier, the escape-competition effect tends to be stronger. Zhou (2009) and Bessen & Maskin (2009) analyze imitation and appropriability conditions. Both studies come to the conclusion that weak patent protection might be superior under certain circumstances (if competition is moderate, respectively if innovation is sequential and competitors’ R&D complementary to own R&D efforts) as weak protection not only leads to more imitation, but imitation also to more innovation (see also Barbosa et al. 2014 for a survey of this literature). A further theoretical branch emphasizes differences with respect to human capital endowment. For example, Vandenbussche et al. (2006) analyze a theoretical model showing that skilled labour has a higher growth-enhancing effect closer to the technological frontier under the reasonable assumption that innovation is a relatively more skill-intensive activity than imitation.

Although recent theoretical literature has noted the importance of imitation, empirical studies explicitly dealing with the imitation-innovation antagonism are scarce. Furthermore, little attention has been given to possible differences between imitating and innovating firms with respect to the relevance of external knowledge and the ways firms acquire such knowledge. Therefore, the main objective of this paper is to identify characteristics of imitation and innovation and shed light on possible differences between these two kinds of innovative activity. It tries to answer the following questions:

- What are the determinants of imitative performance compared to determinants of innovative performance?
- What are the determinants of switching from imitative to innovative behavior compared to imitators and innovators showing persistence over time?

In the first part of the paper, we investigate the differences with respect to the determinants of innovation performance between 'innovators' (INNOV: firms reporting a positive sales share with 'products new to the market') and 'imitators' (IMIT: firms reporting a positive sales share with 'products new to the firm). We use the sales share of these categories of products to measure the intensity of 'innovating' and 'imitating' activities, respectively. Based on theoretical and empirical literature, we distinguish a number of determinants (or groups of determinants) of innovation performance that reflect the 'canon' of determinants of innovation performance (see Cohen 2010 for an excellent survey of related empirical literature). These determinants comprise the endowment in human and physical capital; acquisition of innovation-relevant knowledge from internal and external sources, appropriability conditions, and last but not least, market conditions such as demand in the product market, market structure, and intensity of market competition. In this paper, we mainly focus on the endowment in human capital and the modes of knowledge acquisition.

In a second, more exploratory part of the paper, we investigate the differences with respect to the determinants of innovation performance among several groups of innovating firms that either show 'occasional' or 'persistent' imitative or innovative activity over time (in the sense these two terms are understood in this paper). Moreover, we investigate the 'switching' behaviour of firms from non-innovation, imitation and innovation and conversely over time. The comparison of these groups aims at refining the profiles of innovators and imitators as they emerge from the analysis in the first part of the paper.

Data is drawn from three cross-sections of the Swiss Innovation Panel (SIP), a survey very close to the CIS. It is based on a survey among Swiss firms, has taken place every three years so far and offers unbalanced panel data on innovative activities in the manufacturing and in the services sector. Switzerland might be an interesting case because it is a small economy that ranks very high in terms of innovativeness (see, e.g., European Commission, 2014). At the same time, it is a small economy where not all sectors can be technologically leading and where imitation from foreign firms must take place.

The paper contributes to existing literature in two ways: (a) the investigation is based on a comprehensive set of determinants of differences between innovators and imitators where the focus is on human capital endowment and modes of knowledge acquisition; (b) it examines differences among groups of imitators and innovators with different time profiles with respect to persistence and continuity of innovation performance.

The paper is structured as follows: Section 2 gives a literature review on the definitions of different forms of innovation, determinants of innovation and imitation, and knowledge spillovers. Section 3 describes the data, develops our research hypotheses, and describes the variables and econometric models we use. Section 4 is dedicated to the results. Section 5 presents results for the supplementary analysis we conduct with respect to persistence of innovative activity. Section 6 concludes.

2. Literature review

2.1 General conceptual background

A common problem especially of empirical literature is that confusing definitions of different forms of innovative activity are used as the terms incremental innovation, imitation, and 'new-to-firm' innovation on the one hand and radical innovation, drastic innovation and 'new-to-market' innovation on the other hand are often used in parallel. Particularly, the notions of 'new-to-market' innovation and 'radical innovation', respectively, have received attention in literature, whereas incremental innovations are supposed to be a kind of residual, the remainder of innovations that are not comprised by the definition of radical innovations.

Radical inventions introduce new concepts that depart significantly from prior and current inventions and have the potential to generate new markets and to influence future inventions (Dahlin & Behrens, 2005). Chandy and Tellis (2000) define them as new products that incorporate a substantially different core technology and provide substantially higher customer benefits relative to the previous product generation. According to Garcia and Galantone (2002), radical innovations result in discontinuities in technology and create new demand leading to new competitors, markets and industries.

Drawing on these definitions, incremental innovations are supposed to be inventions that introduce concepts that are already common and can be directly derived from prior and current inventions. They do not have the potential to generate new markets, might not provide substantially higher customer benefit and are strongly influenced by past inventions.

Imitations are mainly incremental innovations that have to be directly related to innovations introduced by competitors and not solely to past inventions of the focal firm. In this paper, we use ‘new-to-firm’ innovation performance as a direct outcome of imitative activity (although we do not directly observe imitative activity).[1]

2.2 Determinants of innovation and imitation

Early literature in Industrial Organization (IO) mainly focused on two determinants of innovation going back to Schumpeter: firm size and market structure. Most importantly, the patent-races literature is concerned with innovators simultaneously racing for making the next invention first (e.g., Reinganum, 1983, 1985). An incumbent might invest less into a given project than a challenger due to the *replacement effect*: The monopolist is already earning positive profits before innovating, whereas the potential entrant does not. The monopolist therefore has lower incentives to innovate compared to the entrant and it is likely that the monopolist will be replaced. If instead the *efficiency effect* dominates in such models, there is a tendency for persistence of a monopoly, as the monopolist will spend more on R&D because he has more to lose than the competitor (see Tirole, 1988, p. 385). The assumption of replacement of previous by subsequent inventors captures the typical Schumpeterian process of creative destruction by assuming that the inventor receives all profit flows, whereas the loosing firm gains nothing (Reinganum, 1985).

There has been also a growing body of research on sequential innovation, beginning with Scotchmer (Scotchmer, 1991), who notes that almost every invention builds on a preceding one. In contrast to most of these models that assume vertical product differentiation over time[2], Bessen & Maskin (2009) consider horizontal product differentiation of follow-on innovations. They argue that some of the most innovative industries’ products like software, PCs and semiconductors have had weak patent protection until recently and experienced rapid imitation because innovations in these industries are both *sequential* and *complementary*. They show that a firm benefits from imitation because by conducting R&D too, the imitating firm raises the probability of new invention.

The principle of leapfrogging from patent races literature has been also applied in Schumpeterian Growth Theory which predicts a negative relationship between competition

[1] The investigation of forms, the degree and the channels of imitation is not a topic of the paper.

[2] See Scotchmer (1996), Scotchmer & Green (1990), Green & Scotchmer (1995), Chang (1995), O'Donoghue (1998), O'Donoghue et al. (1998).

and innovation and productivity growth[3] (Aghion & Howitt, 1992, Grossman & Helpman, 1991). In the theory of step-by-step innovation, a laggard firm first has to catch up with a technological leading firm before racing for a new invention. Aghion et al. (2001) shows that the Schumpeterian (efficiency) effect is always outweighed by the increased incentive for firms to innovate in order to escape competition when technological laggards must first catch up with the leading technology before they can race for the next invention. In Aghion et al. (2005), competition encourages so-called neck-and-neck firms to innovate more rapidly if the competition is low at the beginning, thereby discouraging laggard firms when competition is intense enough. Un this case, laggards have little hope of improving their competitive situation and do not want to waste resources by attempting to innovate. In an industry with neck-and-neck competition, firms automatically catch up with the innovating firm by learning to imitate the current leader's technology. If the degree of competition is very low at the beginning, an increase in competition will result in a faster average innovation rate because the escape-competition effect dominates the Schumpeterian effect. Conversely, if the degree of competition is very high at the beginning, an increase in competition will result in a slower average innovation rate. The authors find support for an inverse U-shaped relationship between competition and innovation as proposed in their theoretical framework. Further, a higher threat of entry encourages innovation by incumbents in technologically advanced sectors and discourages innovation in technologically laggard sectors (Aghion et al., 2009).

From these considerations we can infer that both imitation and innovation should depend on the degree of competition and that the relationship is probably inversely U-shaped – as postulated by the authors cited above – although the exact relationship is hard to determine a priori. At this stage, we can also say that conducting R&D should be related to both imitation and innovation as otherwise imitators might not be able to obtain the tacit knowledge necessary to catch up with the leader.

2.3 Spillovers and Imitation

Beginning with D'Aspremont and Jacquemin (1988) and Jaffe (1986), there has been a growing literature on spillovers and innovation, both theoretically and empirically. Economic growth literature has also begun to focus on knowledge spillovers (Romer, 1986, Romer,

[3] Aghion & Griffith (2005) provide an excellent survey on the foundations of Endogenous Growth Theory in IO, most prominently the circular model of product differentiation of Salop (1977) and the symmetric model of monopolistic competition by Dixit and Stiglitz (1977).

1990, Grossman & Helpman, 1991). Generally, technology spillovers are considered as beneficial for growth and exert a positive externality on productivity of firms and industries, but this perspective neglects the business stealing effect arising from product market rivals doing R&D (Bloom et al., 2013). Knowledge spillovers can be measured – in the simplest way – by constructing a stock of knowledge generated by other firms in the same industry. Another approach that has been applied is using patent citations as a measure for knowledge spillovers (Jaffe, 1986, Jaffe et al., 1993). Spillovers are a major ingredient in the process of diffusion by enabling imitation of competitors. Current research also acknowledges the spillovers' role in creating new innovations. In this line, Cappelli et al. (2014) argue that spillovers from competitors should lead to higher imitation in the industry, whereas spillovers from customers and suppliers may affect both imitation and innovation.

2.4 Open Innovation and Absorptive Capacity

Absorptive capacity describes the ability of a firm to apply new, external information that is critical to its innovative capabilities. A firm's absorptive capacity is a function of the firm's level of prior knowledge. This knowledge is mainly determined by a firm's R&D activity, but the stock of knowledge can be also enhanced by external sources of knowledge (Cohen & Levinthal, 1990). Generally, a firm faces difficulties in applying external knowledge in own R&D projects if the knowledge comes from areas the firm is not familiar with (Jirjahn & Kraft, 2006, p. 2). This knowledge can be utilized, however, if R&D efforts are complementary with competitors' R&D efforts. In this case, imitating firms have the tacit knowledge necessary to improve competitors' products because they worked on similar products in the past. Learning from competitors is much less costly if a firm already produces products which require knowledge that is related to knowledge used in products of rivals.

Building on Cohen and Levinthal, the management literature on 'open innovation' argues that innovative firms draw on knowledge generated by a wide range of external sources (Laursen & Salter, 2006, p. 132; see also Chesbrough, 2003). These external sources typically comprise customers, competitors, suppliers, universities and other external institutions. The idea is that a firm actively searches for external knowledge and that the search process follows a 'search strategy'. Applying knowledge from external sources, a firm might be only able to introduce existing products from competitors or to improve own products rather than producing completely new products. A firm using external knowledge is therefore enabled to catch up with the technological leader, but is not able to push technology beyond this frontier.

Completely new products require drastic innovations which also require rather radical changes in production modes and organizational structure (see Jirjahn & Kraft, 2006).

2.5 Persistence of innovation

Persistence occurs when a firm which has innovated in one period innovates once again in subsequent periods. Empirical literature on this topic is rather scarce (see, e.g., Peters 2009 for a short but comprehensive survey of related literature). Peters herself investigates the persistence question using an innovation panel data set of German manufacturing and service firms for the period 1994-2002. Employing a dynamic probit model she finds that past innovation experience is an important determinant of current innovation activities. In addition, the results demonstrate the relevance of human capital in explaining the persistence of innovation. Based on a dataset covering Ireland and Northern Ireland, Roper and Hewitt-Dundas (2008) find that both product and process innovation are strongly persistent and that larger plants appear to be more able in sustaining innovation than smaller plants, reflecting perhaps resource constraints in smaller plants. In a study based on Swiss panel data, Woerter (2014) shows that persistence with respect to R&D expenditures is more likely to be observed in markets with few principal competitors and is very unlikely to be found in polypolistic markets. There are also studies that cannot confirm the existence of innovation persistence. Geroski et al. (1997) and Raymond (2010) cannot find evidence in support of innovation persistence for UK and Dutch manufacturing firms. These differences can presumably be traced back to differences regarding the innovation measures used (propensity to innovation, sales of innovative products, patents, R&D expenditures, etc.) and the sectors of the economy that are covered by the data used in the studies.

3 Data

The firm level data used in this study were collected in the course of three surveys among Swiss companies conducted in 2005, 2008 and 2011, respectively. All surveys are based on a sample which covers manufacturing industry, construction and the commercial part of the service sector and is (with respect to firm size and two-digit industry affiliation) disproportionately stratified. In this study, we focus on the manufacturing sector because innovations in the service sector are different from innovations in the manufacturing sector (Gallouj & Weinstein, 1997; Tether, 2001). The three surveys yielded data for 2,552, 2,141 and 2,363 firms, representing response rates of 37.9%, 36.1% and 35.9%, respectively. The cross-sections are pooled to a dataset of a total of 3490 observations for the manufacturing sector. The final sample used for model estimation is smaller, primarily due to missing answers for some of the variables. As there is a large time lag between the surveys (three years), only about 50% of the firms replied to two successive surveys, which means that the panel is highly unbalanced.

The three questionnaires, downloadable from www.kof.ethz.ch, contain questions about the firms' innovation activities, innovation success as measured by the sales share with innovations, information on the firms' resource endowment, demand and market conditions, appropriability conditions, technological opportunities and external knowledge acquisition. The surveys also collected information on some financial variables and basic structural characteristics of firms. Table 1 depicts the variables used in our estimations. Descriptive statistics and correlations can be found in Table in the Appendix.

4 Model specification

4.1 Research hypotheses

Innovation versus imitation

Based on existing theoretical and empirical literature, we formulate a series of hypotheses that we intend to investigate in the empirical part of the paper. Our hypotheses refer to (a) human capital endowment as measured by the share of employees with tertiary-level and upper-secondary-level education (vocational training or 'Berufslehre'), respectively; and (b) to modes of knowledge acquisition (in-house R&D, external (or contract) R&D, R&D cooperation, and use of knowledge from different external sources).

Recent studies referring to the concept of the technological frontier (see, e.g., Acemoglu et al. 2006) implicitly deal with differences with respect to human capital requirements between innovation and imitation and can yield useful insights. Starting point of Vandenbussche et al. (2006) is that imitation and innovation require different types of human capital. The authors develop a model in which the relevance of education depends on the distance to the technological frontier. In this model innovation-induced growth is driven by workers with tertiary-level education. Although the model does not refer explicitly to apprenticeship-based vocational education as established in German-speaking countries, we might assume that employees with upper-secondary education belong to the category of employees that do not contribute to innovation. Under this assumption, their model would predict that employees with vocational education are relatively more productive the farther away from the technological frontier the firm operates. The hypothesis that innovation is a relatively more skill-intensive activity than imitation is supported by the empirical part of the study based on a panel dataset covering 19 OECD countries. At firm level, at which empirical evidence is rather scarce, Vinding (2006) finds – in a study with Danish firm data – that the share of highly educated employees is not only positively correlated with innovation but also negatively correlated with imitation. As a consequence we formulate the following hypotheses:

Hypothesis 1a: *The share of highly educated employees as measured by the share of employees with tertiary education is more strongly and positively correlated with innovation than with imitation.*

Hypothesis 1b: *The share of medium-educated employees as measured by the share of employees with vocational education is more strongly and positively correlated with imitation than with innovation.*

From Hypotheses 1a and 1b follows that innovation would be affected more than imitation by a lack of high-skilled employees:

Hypothesis 1c: Innovation is affected more strongly by a lack of high-skilled personnel than imitation.

Using survey data to analyze determinants of innovation, R&D effort is most often reported as a significant determinant of innovation (Mairesse & Mohnen, 2010). In-house R&D is the most important mode of knowledge acquisition for any kind of innovative activity. In-house R&D generates innovation-relevant knowledge but also constitutes a precondition for knowledge absorptive capacity (Cohen and Levinthal, 1989, 1990). Firms with well-educated staff and permanent research activities are supposed to have higher absorptive capacity than firms lacking such characteristics. The exploitation of externally acquired knowledge depends crucially on a firm's absorptive capacity. R&D thus fulfils two roles – as knowledge source and knowledge enabler – and is necessary for both innovation and imitation, whereas the function of new knowledge generation is likely to be more important for innovators than for imitators. There is also empirical evidence that in-house R&D is more intensive in firms that innovate than in those that imitate (see, e.g., Vega-Jurado et al., 2008, Barbosa et al., 2014). Thus, we expect that:

Hypothesis 2: In-house R&D activities are more strongly and positively correlated with innovation than with imitation.

New knowledge is not only generated within the boundaries of a firm but also acquired from the environment. Even the largest and most technologically self-sufficient enterprises require knowledge from beyond the firm boundaries. In addition to own research and development (internal R&D), enterprises typically are engaged in trading of knowledge on the technology market ("buy" or contract external R&D) and/or cooperate actively – formally or informally – with other firms and research institutions. Here, we concentrate on these two modes of knowledge acquisition that are based on explicit formal agreements.[4]

Dhont-Peltrault and Pfister (2011) develop the standardization hypothesis which states that R&D subcontracting is preferred over R&D cooperation when the R&D task to be performed is highly standardized. On the contrary, complex R&D tasks should be more frequently managed through formal R&D cooperation. Thus, it is reasonable to presume that R&D subcontracting is more likely to be found in imitating than in innovating firms. With respect to R&D cooperation there is mixed empirical evidence regarding the hypothesis that innovators acquire external knowledge through R&D collaborations more frequently than imitators. In a study based on UK firm data, Tether (2002) finds that firms that conduct R&D and introduce innovations 'new to the market' rather than 'new to the firm' also engage more frequently in R&D cooperative arrangements. On the contrary, based on German firm data, Aschhoff and Schmidt (2008) find no evidence for such an effect. A possible explanation for these divergences in empirical findings could be that R&D collaborations differ significantly with respect to the type of cooperation partners. Thus, the findings that are based on an overall cooperation variable depend strongly on the composition of the collaborations with respect to the type of partners. Studies distinguishing between various types of cooperation partners (e.g., competitors, suppliers, customers, research institutions, etc.) also find mixed results but mostly of a certain pattern. Based on Belgian firm data, Belderbos et al. (2004) explore R&D cooperation with several categories of partners. Their results confirm that objectives of R&D cooperation are quite heterogeneous. Cooperation with competitors and

[4] For research it is an important task to understand how firms integrate internal knowledge and various types of externally acquired knowledge. The topic of possible complementarities among the various modes of knowledge acquisition has only recently been taken up by economic research (see, e.g., Cassiman & Veugelers, 2006). We refrain from considering this aspect, particularly because a recent study based on the same data that we use in this study could not find any evidence for complementarity between external R&D and R&D cooperation (Arvanitis et al., 2013).

suppliers is focused on incremental innovations; cooperation with competitors and universities is positively correlated with innovations that are new for the market. Aschhoff and Schmidt (2008) also find that R&D cooperation with universities has a positive influence on innovation performance as measured by the sales share with market novelties, while cooperation with other firms do not show any significant effect, neither on innovation nor on imitation (both measured as in the present study). Similar effects of R&D cooperation with universities are found in a study of Monjon and Waelbrock (2003) which is based on French firm data. In our sample, the largest part of the R&D cooperation projects refer to collaborations with firms, so we presume that our cooperation variable COOP reflects primarily the influence of this type of R&D cooperation. Hence, we formulate the following hypotheses:

Hypothesis 3: External R&D is more strongly and positively correlated with imitation than with innovation.

Hypothesis 4: R&D cooperation referring primarily to cooperation with other firms is more strongly and positively correlated with imitation than with innovation.

External knowledge sourcing without formal arrangements is used by many corporations for the acquisition of knowledge that might be combined with own knowledge stocks in order to generate new products and processes. In literature, this kind of knowledge acquisition has been referred to the concept of *technological opportunities* (Klevorick et al., 1995) or, closely related to it, the concept of *incoming spillovers* (Cassiman and Veugelers, 2002). Both concepts refer to the "amount" or extent of external knowledge flows that are beneficial for the firm. Usually, external knowledge sourcing of this kind is operationalized with ordinal measures of the importance of various sources of external knowledge such as customers, suppliers, competitors, universities and other research institutions, publicly available knowledge, etc. The empirical findings with respect to these single sources are mixed depending on the sample of firms on which the studies are based. Amara et al. (2005) explore a sample of Canadian firms and discover that only research as a source of information shows a positive effect on innovation. Jirjahn and Kraft (2011) find positive effects for customers and competitors only for imitators. Their study refers to German firm data from the federal state of Lower Saxony. The authors conclude that "establishments exploit spillovers for incremental innovations rather than for drastic innovations" (p. 509). In a further study with German firms, Cappelli et al. (2014) come to a somewhat different result: information from competitors appears to correlate positively with imitation while information from customers and information from research institutions seems to be more useful for innovators. Köhler et al. (2012) find that science-driven knowledge search is more associated with the share of sales of market novelties, while market-driven search is more related to the share of sales of firm novelties. In accordance with literature we postulate the following hypothesis:

Hypothesis 5: External sourcing is generally more useful for imitators than for innovators except for research sourcing that is more beneficial for innovators rather than for imitators.

Laursen and Salter (2006) do not analyze the effect of single sources of external knowledge, but rather their compound effect. For this purpose they construct two variables, *breadth* and *depth*, measuring the number of sources used and the number of sources used intensively, respectively. Their findings confirm their presumption that "searching widely and deeply across a variety of search channels can provide ideas and resources that help firms gain and exploit innovative opportunities" (p. 146), but 'oversearch' seems to negatively affect innovative performance after reaching a tipping point. External search depth is found to be more related to radical innovation than to incremental innovations. As their research question is also interesting to examine with our sample, we examine similar hypotheses as they do in their paper:

Hypothesis 6a: The 'depth' of external sourcing is more strongly and positively correlated with innovation than with imitation.

Hypothesis 6b: The ‚breadth' of external sourcing is more strongly and positively correlated with imitation than with innovation.

Hypothesis 6c: The 'depth' as well as the 'breadth' of external sourcing shows an inverted U-shaped relationship to innovation performance for both categories.

Occasional versus persistent innovation or imitation

For this exploratory part, the main idea is the differentiation of groups of firms with different patterns of innovation and imitation behavior and the investigation of possible differences with respect to innovation determinants. The interest in this issue is also policy-relevant as a society should be interested in firms' engaging in risky innovation projects persistently in order to generate new and useful products and to stimulate economic growth. If innovation is persistent, innovation-supporting policy measures will have a higher effectivity because they will affect both current and future innovation activities.

In addition to persistent innovators (and imitators), we also study firms that switch from imitative to innovative behavior and the other way around as well as firms that only occasionally report sales with innovative or imitative products (see Table 2 for the composition of our sample with respect to these different firm categories).

Literature on persistence in innovative activity has focused on the role of human capital (Peters, 2009), firm size (Roper & Hewitt-Dundas, 2008) and market structure (Woerter, 2014). With respect to switching firms, i.e. firms switching from non-innovative activity to imitative or innovative activity or firms switching from imitative to innovative activity or conversely, existing literature does not yield any theoretical or empirical guidelines, thus the exploratory character of this part of the paper.

4.2 Definition of variables

Imitation and innovation equations

As already mentioned in the introduction, our dependent variables are (a) innovation performance as measured by firm's innovative sales share of products that are 'new to the market' (INNOV) and (b) imitation performance as measured by firm's sales share of products that are 'new to the firm' (IMIT).[5]

We use a broad range of independent variables in the empirical models (see Table 1 for the exact definition of the variables). We use three different specifications for (a) and (b). They differ with respect to the modelling of the modes of knowledge acquisition and the role of knowledge sources (hypotheses 3 to 5 in section 4.1). In all three specifications we include dummy variables for external (contract) R&D and R&D cooperation and a variable that measures overall technological opportunities as they are anticipated by the firms themselves. In the first specification, we use four dummies indicating whether several knowledge sources have been used at all. We analyze the following four knowledge sources: competitors, suppliers, customers, and non-market external knowledge from institutions, universities, literature, consultants etc. In the second specification, we use four dummies indicating whether the four knowledge sources where important or very important to the firm. These dummies reflect the intensity of the use of each knowledge source. In the third specification, we apply the idea of Laursen and Salter (2006) of summarizing the number of knowledge

[5] Of course, many firms report sales for both categories of innovative products. Therefore, we cannot measure the pure effects of 'innovation' versus 'imitation' which might be the reason that not always clear-cut effects can be found.

sources a firm uses in a variable called *knowledge_breadth* and the number of sources that are important or very important to the firm in a variable called *knowledge_depth*. The values of these variables can range from zero to fourteen as there were fourteen knowledge sources in our survey, initially[6]. This approach enables a direct comparison between the 'quantity' and the 'intensity' in the use of knowledge sources. Following Laursen and Salter, we also include the quadratic terms to examine potentially curvilinear relationships with innovation performance (hypotheses 6a-6c). We used two additional specifications for each variable taking *knowledge_breadth* and *knowledge_depth* separately in order to avoid multicollinearity.

The share of employees with higher education, the share of employees with vocational training and a dummy variable for the importance of lack of qualified personnel as innovation impediment are used as proxies for a firm's human capital endowment (hypotheses 1a to 1c). In-house R&D activities are measured with a dummy variable for in-house R&D (hypothesis 2). Further, we control for gross investments per employee, share of ICT investments and the relevance of lack of funding for innovation as proxies for resource endowment besides R&D and human capital. Further controls refer to demand and market conditions (proxies for demand development, price and non-price competition intensity, the number of competitors), appropriability (measured by easiness of imitation), and general firm characteristics such as firm age, firm size and foreign ownership. To capture industry and time specific effects, we include industry fixed effects and year dummies. As already mentioned, the choice of the control variables follows theoretical literature and is in accordance with previous empirical studies[7].

Occasional versus persistent innovation or imitation

In the second part of the paper, we try to take into account a dynamic dimension by comparing firms innovating from time to time, firms innovating persistently and firms switching back and forth between imitation and innovation. The first group comprises 'occasional innovators', i.e. firms that report sales of innovative products ('new-to-the firm' or new-to the market') from time to time. The second group comprises firms that have changed from imitative to innovative behavior as measured by their sales shares with innovations resp. imitations. The third group is composed of firms that have changed in the

[6] In the first two specifications, we combine the 14 original single knowledge sources to four variables (e.g., suppliers of material/components, equipment and software were combined to 'suppliers').

[7] See Cohen (2010) for a review of research on innovation determinants; see Arvanitis and Hollenstein (1996) and Arvanitis (2008) for empirical studies on innovation determinants based on Swiss firm data.

opposite direction, namely from innovative to imitative behavior. Finally, there are also 'persistent innovators' and 'persistent imitators' comprising firms that have not changed their innovation behavior.

Based on these categories of firms we construct a nominal variable that takes the following values: 0: non-innovators, non-imitators; 1: 'occasional' innovators; 2: imitators that change to innovators as well as innovators that change to imitators ('switchers'); and 3: 'persistent innovators' or 'persistent imitators'. The three innovator/imitator groups are then compared with firms that do not report any sales of innovative products at all (persistent non-innovators) (see Table 1 for the exact definition of the various categories and Table 2 for the composition of our sample with respect to these different firm categories).[8] The specification of the right-hand variables is slightly different compared to the first part: we use lagged variables and only estimate the specification with *knowledge_breadth* and *knowledge_depth*.

4.3 Econometric issues

Method used for the estimation of the innovation equations for INNOV and IMIT

In the empirical literature dealing with sales shares with innovations it is common to estimate Tobit models although the Tobit model is only appropriate for censored data and our data cannot be interpreted as being censored as censoring means that information on the dependent variable has been lost (see Cameron & Trivedi, 2005). In contrast, our dependent variable is a proportion and is bounded between 0 and 1 (resp. 0% and 100%) by definition. For a censored variable, there should exist observations with values lower than 0 or larger than 1 (resp. 100%), but these values should be unobservable so that they are set to 0 or 1[9]. A general problem with the Tobit model is that it requires the error term to be normally distributed and to be homoscedastic. Most of the papers known to us also do not discuss methods dealing with the fact that sales shares are usually only available for innovative firms.

---

[8] The number of switchers from imitation to innovation and conversely (n=96) is small compared to other categories (426 persistent innovators and imitators; 240 occasional innovators; 328 non-innovators). This might be due to the fact that our definition of "true" innovators allows for imitation and innovation activity at the same time, whereas our definition of imitators only allows for imitation activity. Therefore, firms are not required to really switch back and forth, but can innovate persistently with imitations and innovations at the same time. In this sense, switchers from imitation and innovation and conversely might be considered to be persistently innovating firms.

[9] One argument for censoring could be that sales shares with innovations are not observed for non-innovators and that innovation sales shares have to be set to zero for this group of firms. However, other papers generally use only data for innovators. Thus, the proportion sales share cannot be interpreted as being censored.

We follow another econometric approach that requires a minimum of assumptions, provides a large degree of flexibility and can be easily implemented with standard software. For sales share with innovations it is most obvious to use a fractional logit model accounting for the proportional character of the dependent variable as suggested by Papke and Wooldridge (1996). Papke and Wooldridge proposed models for the conditional mean of the fractional response keeping the predicted values in the unit interval. Using quasi-maximum likelihood estimation, they obtained robust estimators of the conditional mean parameters. In our estimations, we have to take into account one complicating factor: Innovation performance as reflected by the sales shares is based on the firm's decision to innovate or not. The reason is that not all firms choose to innovate so that there is a corner solution at zero simply because a firm can only realize sales with innovations if it has innovated at all. Therefore, the quantitative dependent variables measuring innovation performance are measured only for firms which actually have innovation activities. Following Egger & Kesina (2013), Oberhofer & Pfaffermayr (2009), and Ramalho & daSilva (2009), we therefore estimate two-part models. Such a two-part model covers the possibility that variables can affect the decision of being an innovator (activity) and the sales shares (performance) differently. The first part of the model consists of the firm's decision to innovate or not and is specified by a binary outcome model explaining the probability of a firm of being an product innovator. The decision of firm i to introduce product innovations is represented by the binary variable $innopd_i$. The conditional expectation for $innopd_i$ is

$$E(innopd_i \mid x_i) = \Pr(innopd_i = 1) = F(x_i\beta) \tag{1}$$

where x_i denotes the (1xk) vector of determinants of a firm's innovative activity, β is the corresponding (kx1) vector of parameters, and $F(\cdot)$ is a cumulative distribution function. A logit model can be applied with cumulative logistic distribution function $\Lambda(\cdot)$:

$$\begin{aligned}&\Pr(innopd_i = 1 \mid x_i) = \Lambda(\beta_0 + \boldsymbol{\beta}_1 \cdot resources + \boldsymbol{\beta}_2 \cdot demand\_and\_market\_conditions \\ &+\boldsymbol{\beta}_3 \cdot appropriability + \boldsymbol{\beta}_4 \cdot tech\_opportunities\_and\_external\_knowledge\_acquisition \\ &+\boldsymbol{\beta}_5 \cdot controls)\end{aligned} \tag{2}$$

Note that most of the variable groups *resources*, *demand and market conditions*, *appropriability*, *technological opportunities and external knowledge acquisition* comprise several single variables as mentioned in section 4.2 and described in Table 1. Therefore, each beta spans a vector of several parameters that have to be estimated. As mentioned above, the category *technological opportunities and external knowledge acquisition* is specified in three different ways:

1. *tech_pot, know_comp, know_supp, know_cust, rnd_coop, rnd_ext*
2. *tech_pot, know_comp_int, know_supp_int, know_cust_int, rnd_coop, rnd_ext*
3. *tech_pot, know_breadth, know_breadth2, know_depth, know_depth2, rnd_coop, rnd_ext.*

Besides firm size and firm age, the vector of controls contains industry dummies and time dummies.

For the second part of the model, we assume that

$$E(inno\_share_i \mid x_i, innopd_i = 1) = G(x_i\delta) \tag{3}$$

where $G(\cdot)$ is a cumulative distribution function, δ a vector of coefficients, and $inno\_share_i=\{IMIT_i, INNOV_i\}$.

As shown by the aforementioned authors, the conditional mean of $inno\_share_i$ can be decomposed as follows:

$$E(inno\_share_i \mid x_i) = E(inno\_share_i \mid x_i, innopd = 1) \cdot P(innopd = 1 \mid x_i) = G(x_i\delta) \cdot F(x_i\beta) \tag{4}$$

This decomposition of the conditional mean is central because it enables us to estimate both parts separately. The first part is estimated as described in equation (2). The second part of the model (for the sales shares of innovators only) is estimated with a fractional logit model, again using a logistic distribution function:

$$\begin{aligned}&\Pr(inno\_share_i \mid x_i) = \Lambda(\beta_0 + \mathbf{\beta_1} \cdot resources + \mathbf{\beta_2} \cdot demand\_and\_market\_conditions \\ &+\mathbf{\beta_3} \cdot appropriability + \mathbf{\beta_4} \cdot tech\_opportunities\_and\_external\_knowledge\_acquisition \\ &+\mathbf{\beta_5} \cdot controls)\end{aligned} \tag{5}$$

We also estimate the models jointly by pooling the data with zero product innovations and positive sales shares to test whether there are differences to the fractional response model estimated for the subsample of innovators only. Differences would indicate that the "zeroes" are determined by other variables. In our estimations, we pool the three cross sections and estimate cluster-robust standard errors. We use the GLM procedure of STATA. This procedure fits a generalized linear model where the distribution of the dependent variable and the link function can be specified. It does not exploit the panel structure. An alternative would be to use the XTGEE procedure. It fits a generalized linear panel-data model and allows the researcher to specify the within-group correlation structure. Similar to Papke & Wooldridge (2008), we find that, even though the procedure GLM does not exploit the panel structure, it is (almost) as efficient as XTGEE which takes into account the panel structure. For this reason, we only show results for pooled cross sections using cluster-robust standard errors.

Method used for the estimation of the equations for various groups of innovators and imitators

For these estimations, we employ a multinomial logit model for the four mutually exclusive groups of firms (persistent non-innovators, occasional innovators, imitation-innovation switcher, persistent innovators or imitators) using these groups as base category, consecutively. We used lagged regressors to make sure that a variable in *t-1* determines persistent or switching innovation behavior in the period *(t-1, t)*.

Multicollinearity

A potential problem might be multicollinearity between variables referring to R&D activity (in-house R&D, external (contract) R&D, R&D cooperation). We therefore insert these variables separately (only one R&D activity per estimation) to look whether coefficients resp. marginal effects change their signs or become (in)significant. The results (not shown here) are the same with the exception of external R&D whose insignificant positive coefficient becomes significant for INNOV when we do not control for other R&D activities.

Endogeneity

The findings of Garriga et al. (2013) and Laursen & Salter (2014) imply that knowledge breadth and depth must be treated as endogenous and Laursen & Salter provide evidence that external search breadth is positively associated with appropriability. Indeed, in additional regressions not shown here, we also found statistically positive associations between a variable measuring appropriability and knowledge breadth and depth. We added the fitted residual from an OLS regression on 'breadth' and 'depth' (our first stage) to the second part fractional logit model to test for endogeneity. However, this test shows that the hypothesis that knowledge breadth and depth are exogenous cannot be rejected.

The possible endogeneity of the R&D-related variables would also result in biased estimates. However, our estimates include an unusually rich set of control variables. This is likely to mitigate problems of endogeneity (see also Jirjahn & Kraft 2011 for a similar argumentation). Further, it is difficult if not impossible to find variables in our sample that are exogenous also in economic terms and can be used as instruments. So we have to refrain from conducting further endogeneity tests. Therefore, it is not possible to test the existence of causal relations between the independent variables and the dependent variable directly. Nevertheless, some robust regularities emerge which, if interpreted in view of our main hypotheses, could indicate the direction of causal links.

5 Results

5.1 Estimates of the equations for INNOV and IMIT

The results of the fractional two-part logit model only using the subsample of firms with innovation activities are presented in Table 3 (equations for IMIT and INNOV) and in Table A.3 in the appendix (first part logit model for innopd). In Table A.4 in the appendix, estimates of the fractional logit model using all available observations are shown, i.e. including also firms without innovation activities. We estimate average marginal effects for all estimations. For all estimations and similar to Egger & Kesina (2013), we display some criteria to evaluate the estimation quality of the model. For the fractional logit models we use the correlation of actual and predicted outcomes and the Akaike criterion. For the logit model in the first part we apply the correlation of actual and predicted outcomes, and, additionally, McFadden's pseudo R^2, the 'sensitivity' criterion explaining the fraction of innovators correctly predicted by the model, the 'specificity' criterion explaining the fraction of non-innovators correctly predicted by the model, and the percentage of correctly predicted outcomes in total. The criteria are depicted at the bottom of the results tables.

Resource endowment

In accordance with *hypothesis* 2, the marginal effect of R&D is positive and significant only in the equation for INNOV. The same is true for the marginal effect of the share of employees with higher education (highly educated employees). Conversely, the share of employees with vocational training (medium-educated employees) is only significantly associated with the sales share with imitations. These findings seem to support *hypotheses 1a* and *1b* respectively. Impediments with respect to the endowment with skilled labor or financing (both internal and external) are not found to be statistically relevant for innovation performance. Thus, hypothesis 1c is not confirmed by these findings.

For the other variables characterizing resource endowment, only the share of ICT investments shows significantly positive associations with both dimensions of innovation performance, but to a higher degree with the sales share with imitations. The proxy for investments in physical assets (gross investment per employee) is not found to be statistically relevant for innovation performance.

Using the whole sample for estimation, R&D is found to exert a significant effect on both imitation and innovation performance (Table A.4 in the appendix). This result is obviously driven by the large effect on the probability of innovating with new products that R&D has in the first part. It supports our approach to only consider innovators in the second part, as the second part estimation might be driven by other factors than the first part. The shares of employees with higher education and with vocational training, the impediments with respect to skills and financing, and the investment variables, however, do not behave differently in the estimation for the whole sample.

Demand and market conditions

Interestingly, demand and market conditions as measured in the survey seem to play virtually no role for innovation success, except for non-price competition that has a marginal effect on INNOV that is significant on the 10% test level. In the whole sample analysis we also find significantly positive effects of a medium number of competitors in the market. This result, however, might be driven by the first part where all levels of competition exert significant effects on the probability to innovate.

Appropriability conditions

Appropriability is measured by the variable 'easiness of imitation', but it neither plays a role for the sales shares with innovations nor for the propensity to innovate.

Technological opportunities & knowledge acquisition

Technological potential is a variable capturing the degree to which a firm draws on existing technological knowledge comprising knowledge from basic research, knowledge on key technologies and the transformation into innovations on the market, and specific knowledge that is targeted to a certain field of activity. It is only found to be significantly related with IMIT but not with INNOV. This suggests that firms that are successful with market innovations prefer to generate new knowledge by their own rather than draw on the publicly available knowledge stock. This interpretation is underpinned by the result that R&D cooperation does play a role for IMIT but not for INNOV. The same is true for firms doing external R&D. If we distinguish R&D cooperation with firms and R&D cooperation with research institutions, it can be additionally shown that only R&D cooperation with other firms is positively correlated with the sales share with imitations[10]. These findings are in accordance with *hypothesis 3* and *hypothesis 4,* respectively. To conclude, the explicit forms of

[10] These auxiliary regressions are not shown here.

knowledge acquisition (R&D cooperation; external (contract) R&D) seem to be only relevant for imitation performance. In contrast, knowledge created with own resources, i.e. by internal R&D and highly qualified employees, is relevant for market novelties.

For single knowledge sources, we find a highly significantly positive effect of the use of customers as a knowledge source on INNOV. A similar effect is also found in Cappelli et al. (2014) for German firms. No effect is found for sources other than firms (including research institutions). The use of single sources does not show significant effects on IMIT. A further test shows that the four source variables in column 1 and 2 in Table 3 are jointly significant in the estimates of the innovation equation but not in the estimates of the imitation equation. This finding is contrary to hypothesis 5.[11] *Hypothesis 5* does not receive any empirical confirmation.

Astonishingly, we find a negatively significant effect of the knowledge source external institutions and science on the probability to innovate in the first part of the model. The effect is not significant in the second part. In order to better understand this finding, we run additional regressions (not shown here) where we split the sample into low-tech industry firms and high-tech industry firms. The results show that the effect of external knowledge from sources other than firms on the probability to innovate is only significantly negative in the logit regression for low-tech industry firms. Further, the effect of customers on INNOV is considerably higher in the subsample of low-tech industry firms[12]. These findings demonstrate that there is some sectoral heterogeneity, even if we control for industries at the 2-digit level. We conclude that the use of customers' knowledge is significantly more effective in low-tech than in high-tech industries.

Contrary to single sources, the number of sources used as represented in the 'breadth' variable do matter for imitation performance which is in accordance with *hypothesis 6b* (hypothesis of Laursen & Salter, 2006). We also observe a curvilinear relationship (inversely U-shaped) of this variable with respect to imitation (*hypothesis 6c*). This corroborates the view that imitators draw on a variety of external sources rather than targeting specific sources. This unspecific knowledge search behavior is not observed for market innovators where 'breadth'

[11] The same test for the estimates of the model version in column 3 and 4 showed no joint statistical significance for the four source variables, thus indicating that this finding is not very robust.

[12] A further interesting finding from this subsample analysis is that R&D activities (internal, external and in cooperation), and qualification of the labor force do not play a role for sales shares with innovations and imitations in low-tech industries. Grimpe and Sofka (2009) also find that search patterns in low-technology industries focus on market knowledge (customers and competitors). However, their finding that high-technology industries target universities is not supported by our findings.

does not exert a significant effect. The effect of the overall intensity of knowledge sourcing as represented by the 'depth' variable is slightly significant for imitation performance (only the linear term). This linear term is also slightly significant for INNOV if we estimate 'breadth' and 'depth' separately. Contrary to the findings of Laursen & Salter (2006), *hypotheses 6a* and *6c* are therefore only partly confirmed by our findings.[13]

On the whole, imitating firms seem to be significantly more 'extroverted' than innovating firms that base their activities mostly on in-house R&D and personnel with tertiary-level education. More precisely, their performance as measured by the sales share of products-new-to-firm depends significantly on external sourcing (without any particular propensity to a specific knowledge source) and engagement in R&D cooperation and external R&D. The rather 'introverted' behavior pattern of innovating firms is more difficult to understand. Given that a firm is able to launch market novelties, it seems that its performance (as measured by the sales shares of such novelties) does not depend on the intensity of external sourcing (which does not mean that the firm does not use external knowledge at all). This finding is in accordance with a strand of literature that presumes that 'radical' innovations are not predominantly created by searching external knowledge but by an innovator's successful commercialization of a single unique idea (see, e.g., Garriga et al. 2013).

Further variables

Firm size does not seem to have an effect on our performance measures. For INNOV, we find a negative effect of firm age that is highly significant meaning that younger firms have higher sales shares of market novelties than older ones. This effect is only driven by innovative firms as can be seen from the first part of the model where firm age is insignificant. For IMIT, the effect of firm age is insignificant in all parts of the model. In most specifications, foreign ownership is positively significantly associated with the sales share with imitations, i.e. foreign-owned firms' innovation activities seem to be targeted on imitations to larger degree than domestic firms' activities. An explanation could be that for most foreign-owned firms the R&D department is located in the country of the mother firm.

5.2 Robustness

[13] Garriga et al. (2013) used the same source of data as we did, but considered firms from both the manufacturing and the service sector and used only one cross-section. With respect to knowledge breadth and depth their results are very similar to ours.

An important robustness check is the comparison of estimates based on the subsample for innovating firms with the estimates for the whole sample including all non-innovating firms for which both INNOV and IMIT are zero. The results show that all marginal effects that are significant for innovators only are also found to be significant in the whole sample estimation. This supports our believe that the significant marginal effects from the analysis of the subsample of innovating firms are in fact relevant and robust. Differences related to marginal effects that are only found to be statistical significant in the whole sample can be attributed to the first part, namely the decision to innovate or not (equation for *innopd*).

Further, estimation with pseudo-maximum likelihood requires the conditional means to be specified correctly. We can test the functional form of the conditional mean by means of a link test: "It regresses a dependent variable y_i on $\hat{y}_i$ (i.e. the model prediction of y_i) and $\hat{y}_i^2$ without the original explanatory variables and tests whether the coefficient of $\hat{y}_i^2$ is zero or not." (Egger & Kesina 2013). A non-zero coefficient would imply that the model is misspecified with respect to the conditional mean. However, the link tests (shown at the bottom of the estimation results in the respective tables) cannot be rejected with respect to the hypotheses that the coefficient of $\hat{y}_i^2$ is zero for any estimation. The only exception is the third specification of the logit model in the first part where the coefficient is significant at the 10% significance level. In general, the link tests show that we do not have to worry about misspecification of the conditional means.

5.3 Estimates for various groups of innovators/imitators

Table 4 contains the estimates of the multinomial logit model for the three groups of 'occasional innovators/imitators', 'switchers' between imitation and innovation and 'persistent innovators/imitators' as compared with firms without any innovative activities. We discuss the results for each group of innovation determinants separately. The discussion aims at sketching a behavior pattern for every category according to the estimated effects of the various determinants. We find it reasonable to presume that there is a kind of innovation performance hierarchy that goes from occasional innovators through switchers to persistent innovating firms. Thereby, differences between the coefficients of the various determinants for these three categories of innovating firms can be also considered under this perspective.

Resource endowment

R&D activities correlate more strongly with switchers and persistently innovating firms than with occasionally innovating firms. This seems to be also the case for the proxy for physical capital but not for the share of ICT investment which is more strongly positively correlated with occasional and persistent innovators (or imitators) than with switchers. Lack of funding also appears to affect occasional innovators and persistent innovators alike but not switchers. The funding requirements for these two quite different groups might be not the same: occasional innovators have to invest some resources to *start* innovation activities, persistent innovators need some *additional* investment to *sustain* their innovating activities, whereas switchers do not differ from non-innovators regarding the funding behavior. We find no differences among the three groups as compared with non-innovators with respect to human capital which can be interpreted as a hint that inadequate endowment with human capital might not be the main reason for Swiss firms not to innovate.

Demand and market conditions

Demand cannot explain differences among innovating and non-innovating firms as well as among the three groups of innovating firms. The same appears to be the case for the intensity of price competition. More intense non-price competition, however, correlates with the likelihood to innovate persistently. Market structure is not associated with the likelihood to switch, whereas it strongly correlates with the likelihood of innovating persistently or at least occasionally compared to not innovating. The effect on occasional innovative activity is strongest for a very small number of competitors (up to five) and on persistence strongest for a medium number of competitors (6-50). Persistent innovators are thus more likely to be found in markets with less than 50 competitors, i.e. in markets with moderate or strong oligopolistic structure. This finding is consistent with the results of Woerter (2014).

Appropriability conditions

A lack of protection of innovations from imitation generally affects innovative activity negatively for all three categories of innovating firms, quite in accordance with standard theoretical expectations.

External knowledge acquisition and technological opportunities

There are not any differences with respect to the anticipation of technological possibilities as measured by the variable ‘technological potential’ among innovating and non-innovating firms. The same is true among the three groups of innovating firms. This might indicate that information with respect to technological chances is not unevenly distributed among Swiss firms. However, there are differences with respect to the use of formal external sources of knowledge among the different groups of innovating firms and between non-innovators and innovators: First and not surprisingly, more external R&D and R&D cooperation increase the likelihood of switching and innovating persistently compared to non-innovating, but not of innovating occasionally. Second, more external R&D and R&D cooperation also increase the likelihood of switching or innovating persistently compared to innovating occasionally.

For the three groups of innovating firms that are distinguished here, the hypotheses of Laursen & Salter (2006) are only partly confirmed (but of course, they are examined in a quite different setting here). There are no differences regarding the depth of external knowledge sourcing. The expectation would be rather that this variable would increase the likelihood of persistence compared to the other two groups. Furthermore, the inversely U-shaped pattern with respect to breadth of external sourcing is only found for occasional innovators compared to non-innovators.

Further variables

There is a positive size effect on the likelihood of persistence compared to non-innovators but no age effect. Consistent with the first part of the paper, foreign ownership makes firms to be more likely to be non-innovators compared to the three groups of innovating firms.

6 Summary and conclusions

The main purpose of this paper was to characterize imitative and innovative behavior and shed light on possible differences. We analyzed a broad spectrum of possible determinants of imitation and innovation and the corresponding innovation performance. We found that variables pertaining to resource endowment, technological opportunities and external knowledge acquisition are most important in contributing to either imitation or innovation. Internal knowledge and resources are more relevant for 'new-to-market' innovations, whereas externally acquired knowledge (including contract R&D and R&D cooperation) are more relevant for 'new-to-firm' innovations. We found that the breadth of external knowledge sources is a more important determinant of 'new-to-firm' innovation than the use of any single source or the intensity of the use of any single knowledge sources. Most important, 'new-to-firm' performance is strongly related to unspecific knowledge acquisition, namely to the so-called technological potential that is publicly available non-tacit technological knowledge.

In sum, our findings indicate that imitating firms are significantly more 'extroverted' than innovating firms because their activities are much more related to external R&D activities and cooperation and personnel with upper secondary-level education. Innovating firms do not rely to the same extent on the exploration of external knowledge. Their rather 'introverted' behavior seems be more related with intense exploitation of internal resources. In addition, firms with foreign parent company tend to perform with imitations, whereas younger firms tend to perform with market novelties.

Although the literature on the competition-innovation relationship is fruitful for the establishment of an important role of imitation with respect to innovative activity, our results do not support relationships between competition and innovation performance as measured in this study. Variables that are attached to the literature on spillovers and open innovation are found to play a more important role although our results do not coincide with former findings in every respect.

A second, more exploratory goal of the paper, was the investigation of the differences with respect to the determinants of innovation performance among three different groups of innovating firms with different innovation behavior over time ('occasional' innovators or imitators; switchers from imitation to innovation and conversely; 'persistent' innovators or imitators). The comparison of these groups aimed at refining the profiles of innovators and imitators as they emerge from the analysis in the first part of the paper. We found more differences between occasional innovators and the other two groups (switchers and persistent innovators) than between switchers and persistent innovators (as compared to non-innovators). Resource endowment (R&D, gross investment per employee) is more strongly associated with switchers and persistent innovators than with occasional innovators. Appropriability is also more important for switchers and persistent innovators than for occasional innovators. Finally, external R&D and R&D cooperation is more relevant for these two groups than for occasional innovators. On the whole, out of these profiles an innovation performance hierarchy emerges ranking from occasional innovators through switchers to persistently innovating firms.

Literature

Acemoglu, D., Aghion, P., & and Zilibotti, F. (2006). Distance to Frontier, Selection, and Economic Growth. *Journal of the European Economic Association*, 4(1), 37-74.

Aghion, P., & Griffith, R. (2005). *Competition and Growth - Reconciling Theory and Evidence.* Cambridge, MA: The MIT Press.

Aghion, P., & Howitt, P. (1992). A Model of Growth through Creative Destruction. *Econometrica, 60*, 323-351.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics, 120(2)*, 701-728.

Aghion, P., Blundell, R., Griffith, R., Howitt, P., & Prantl, S. (2009). The Effects of Entry on Incumbent Innovation and Productivity. *The Review of Economics and Statistics, 91(1)*, 20-32.

Aghion, P., Harris, C., Howitt, P., & Vickers, J. (2001). Competition, Imitation and Growth with Step-by-Step Innovation. *Review of Economic Studies, 68(3)*, 467-492.

Amara, N., & Landry, R. (2005). Sources of Information as Determinants of Novelty of Innovation in Manufacturing Firms - Evidence from the 1999 Statistics Canada Innovation Survey. *Technovation, 25(3)*, 245-259.

Arvanitis, S. (2008). Innovation and Labour Productivity in the Swiss Manufacturing Sector: An Analysis Based on Firm Panel Data. In C. van Beers, A. Kleinknecht, R. Ortt, & R. Verburg, *Determinants of Innovative Behaviour* (pp. 188-216). Palgrave Macmillan.

Arvanitis, S., & Hollenstein, H. (1996). Das Innovationsprofil der Schweizer Industrie: Determinanten, Zielorientierung und Hemmnisfaktoren der Innovationstätigkeit. *Schweizerische Zeitschrift für Volkswirtschaft und Statistik, 132(3)*, 335-358.

Arvanitis, S., Lokshin, B., Mohnen, P., & Wörter, M. (2013). Impact of External Knowledge Acquisition Strategies on Innovation - A Comparative Study Based on Dutch and Swiss Panel Data. *KOF Working Paper Nr. 325*.

Aschhoff, B., & Schmidt, T. (2008). Empirical Evidence on the Success of R&D Cooperation - Happy Together? *Review of Industrial Organization, 33(1)*, 41-62.

Barbosa, N., Faria, A. P., & Eiriz, V. (2014). Industry- and Firm-Specific Factors of Innovation Novelty. *Industrial and Corporate Change, 23(3)*, 1-38.

Belderbos, R., Carree, M., & Lokshin, B. (2004). Cooperative R&D and Firm Performance. *Research Policy, 33*, 1477-1492.

Bessen, J., & Maskin, E. (2009). Sequential Innovation, Patents, and Imitation. *The RAND Journal of Economics, 40(4)*, 611-635.

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica, 81:4*, 1347-1393.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics - Methods and Applications.* Cambridge: Cambridge University Press.

Cappelli, R., Czarnitzki, & Kraft, K. (2014). Sources of Spillovers for Imitation and Innovation. *Research Policy, 43:1*, 115-120.

Cassiman, B., & Veugelers, R. (2002). R&D Cooperation and Spillovers - Some Empirical Evidence from Belgium. *The American Economic Review, 92(4)*, 1169-1184.

Cassiman, B., & Veugelers, R. (2006). In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition. *Management Science, 52(1)*, 68-82.

Chandy, R. K., & Tellis, G. J. (2000). The Incumbent's Curse? Incumbency, Size, and Radical Product Innovation. *Journal of Marketing, 64(3)*, 1-17.

Chang, H. (1995). Patent Scope, Antitrust Policy, and Cumulative Innovation. *The RAND Journal of Economics, 26(1)*, 34-57.

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

Cohen, W. M. (2010). Fifity Years of Empirical Studies of Innovative Activity and Performance. In B. H. Hall, & N. Rosenberg, *Handbook of The Economics of Innovation* (pp. 129-213). Amsterdam: Elsevier.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R&D. *Economic Journal, 99*, 569-596.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive Capacity - A New Perspective on Learning and Innovation. *Administrative Science Quarterly; 35:1*, 128-152.

Dahlin, K. B., & Behrens, D. M. (2005). When is an Invention Really Radical? Defining and Measuring Technological Radicalness. *Research Policy, 34*, 717-737.

D'Aspremont, C., & Jacquemin, A. (1988). Cooperative and Noncooperative R&D in Duopoly with Spillovers. *The American Economic Review*, 1133-1137.

Dhont-Peltraut, E., & Pfister, E. (2011). R&D Cooperation versus R&D Subcontracting: Empirical Evidence from French Survey Data. *Economics of Innovation and New Technology, 20(4)*, 309-341.

Dixit, A. K., & Stiglitz, J. E. (1977). Monopolistic Competition and Optimum Product Diversity. *The American Economic Review, 67(3)*, 297-308 .

Egger, P., & Kesina, M. (2013). Financial Constraints and Exports - Evidence from Chinese Firms. *CESifo Economic Studies, 59(4)*, 676-706.

European Commission. (2014). *Innovation Union Scoreboard 2014.* European Union.

Gallouj, F., & Weinstein, O. (1997). Innovation in Services. *Research Policy, 26*, 537-556.

Garcia, R., & Calantone, R. (2002). A Critical Look at the Technological Innovation Typology and Innovativeness Terminology: A Literature Review. *The Journal of Product Innovation Management, 19*, 110-132.

Garriga, H., von Krogh, G., & Spaeth, S. (2013). Research Notes and Commentaries - How Constraints and Knowledge Impact Open Innovation. *Strategic Management Journal, 34(9)*, 1134-1144.

Geroski, P. A., Van Reenen, J., & Walters, C. F. (1997). How Persistently do Firms Innovate? *Research Policy, 26(1)*, 33-48.

Green, J., & Scotchmer, S. (1995). On the Division of Profit in Sequential Innovation. *The RAND Journal of Economics, 26(1)*, 20-33.

Grimpe, H., & Sofka, W. (2009). Search Patterns and Absorptive Capacity - Low- and High-Technology Sectors in European Countries. *Research Policy, 38(3)*, 495-506.

Grossman, G. M., & Helpman, E. (1991). *Innovation and Growth in the Global Economy.* Cambridge, MA: MIT Press.

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R&D - Evidence from Firms' Patents, Profits, and Market Value. *The American Economic Review, 76:5*, 984-1001.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics, 108(3)*, 577-598.

Jirjahn, U., & Kraft, K. (2011). Do Spillovers Stimulate Incremental or Drastic Product Innovations? Hypotheses and Evidence from German Establishment Data. *Oxford Bulletin of Economics and Statistics, 73(4)*, 509–538.

Kleinknecht, A., Van Montfort, K., & Brouwer, E. (2002). The Non-Trivial Choice between Innovation Indicators. *Economics of Innovation and New Technology, 11(2)*, 109-121.

Klevorick, A. K., Levin, R. C., Nelson, R. R., & Winter, S. G. (1995). On the Sources and Significance of Interindustry Difference in Technological Opportunities. *Research Policy, 24(2)*, 185-205.

Köhler, C., Wofka, W., & Grimpe, C. (2012). Selective Search, Sectoral Patterns, and the Impact on Product Innovation Performance. *Research Policy, 41(8)*, 1344-1356.

Laursen, K., & Salter, A. (2006). Open for Innovation - The Role of Openness in Explaining Innovation Performance among UK Manufacturing Firms. *Strategic Management Journal; 27:2*, 131-150.

Laursen, K., & Salter, A. J. (2014). The Paradox of Openness - Appropriability, External Search and Collaboration. *Research Policy, forthcoming*, 1-12.

Mairesse, J., & Mohnen, P. (2010). Using Innovation Surveys for Econometric Analysis. In B. H. Hall, & N. Rosenberg, *Handbook of The Economics of Innovation* (pp. 1129-1155). Amsterdam: Elsevier.

Monjon, S., & Waelbroeck, P. (2003). Assessing Spillovers from Universities to Firms - Evidence from French Firm-level Data. *International Journal of Industrial Organization, 21(9)*, 1255-1270.

Oberhofer, H., & Pfaffermayr, M. (2009). Fractional Response Models - A Replication Exercise of Papke and Wooldridge (1996). *Working Papers in Economics and Statistics, No. 2009-02*.

O'Donoghue, T. (1998). A Patentability Requirement for Sequential Innovation. *The RAND Journal of Economics, 29(4)*, 654-679.

O'Donoghue, T., Scotchmer, S., & Thisse, J.-F. (1998). Patent Breadth, Patent Life, and the Pace of Technological Progress. *Journal of Economics & Management Strategy, 7(1)*, 1-32.

Papke, L. E., & Wooldridge, J. M. (1996). Econometric Methods for Fractional Response Variables with an Application to 401(k) Participation Rates. *Journal of Applied Econometrics, 11(6)*, 619-632.

Papke, L. E., & Wooldridge, J. M. (2008). Panel Data Methods for Fractional Response Variables with an Application to Pass Rates. *Journal of Econometrics, 145(1-2)*, 121-133.

Peters, B. (2009). Persistence of Innovation: Stylised Facts and Panel Data Evidence. *Journal of Technology Transfer, 34(2)*, 226-243.

Ramalho, J. J., & daSilva, J. V. (2009). A Two-part Fractional Regression Model for the Financial Leverage Decisions of Micro, Small, Medium and large Firms. *Quantitative Finance, 9(5)*, 621-636.

Raymond, W., Mohnen, P., Palm, F., & van der Loeff, S. S. (2010). Persistence of Innovation in Dutch Manufacturing - is it Spurious. *The Review of Economics and Statistics, 92(3)*, 495-504.

Reinganum, J. R. (1983). Uncertain Innovation and the Persistence of Monopoly. *The American Economic Review, 73(4)*, 741-748.

Reinganum, J. R. (1985). Innovation and Industry Evolution. *The Quarterly Journal of Economics, 100(1)*, 81-99.

Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy; 94:5*, 1002-1037.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy; 98:5*, S71-S102.

Roper, S., & Hewitt-Dundas, N. (2008). Innovation persistence - Survey and case-study evidence. *Research Policy, 37(1)*, 149-162.

Salop, S. C. (1977). The Noisy Monopolist - Imperfect Information, Price Dispersion, and Price Discrimination. *Review of Economic Studies*, 393-406.

Scotchmer, S. (1991). Standing on the Shoulders of Giants: Cumulative Research and the Patent Law. *The Journal of Economic Perspectives, 5(1)*, 29-41.

Scotchmer, S. (1996). Protecting Early Innovators: Should Second-Generation Products be Patentable? *The RAND Journal of Economics, 27(2)*, 322-331.

Scotchmer, S., & Green, J. (1990). Novelty and Disclosure in Patent Law. *The RAND Journal of Economics, 21(1)*, 131-146.

Tether, B. (2001). Identifying Innovation, Innovators and Innovative Behaviours: A Critical Assessment of the Community Innovation Survey (CIS). *CRIC Discussion Paper No. 48*.

Tether, B. (2002). Who Co-operates for Innovation, and why - An Empirical Analysis. *Research Policy, 31(6)*, 947-967.

Tirole, J. (1988). *The Theory of Industrial Organization.* Cambridge, MA: The MIT Press.

Vandenbussche, J., Aghion, P., & Meghir, C. (2006). Growth, Distance to Frontier and Composition of Human Capital. *Journal of Economic Growth, 11(2)*, 97-127.

Vega-Jurado, J., Gutiérrez-Gracia, A., Fernandez-de-Lucio, I., & Manjarrés-Henriquez. (2008). The Effect of External and Enternal Factors on Firms' Product Innovation. *Research Policy, 37(4)*, 616-632.

Vinding, A. L. (2006). Absorptive Capacity and Innovative Performance: A Human Capital Approach. *Economics of innovation and New Technology, 15(4/5)*, 507-517.

Woerter, M. (2014). Competition and Persistence of R&D. *Economics of Innovation and New Technology, forthcoming*.

Zhou, W. (2009). Innovation, Imitation and Competition. *The B.E. Journal of Economic Analysis & Policy, 9(1)*, Article 27.

Tables

Table 1: List of Variables

Variable	Description
Dependent variables	
Innopd	Firm has introduced product innovation during last three years, 1 yes / 0 no
IMIT	Sales share with product innovations new to the firm
INNOV	Sales share with product innovations new to the market
Resource endowment	
Rnd	Firm has conducted R&D during the last three years, 1 yes / 0 no (dummy variable is 0 for all non-innovators)
Lnempl_shr_higher	Share of employees with higher education, ln
Lnempl_shr_train	Share of employees with vocational training, ln
Skill_imped	Lack of skilled employees as an important or very important impediment for innovation activities, 1 yes / 0 no
Fin_imped	Lack of internal or external funding as an important or very important impediment for innovation activities, 1 yes / 0 no
Lninvest_pc	Gross investments per employee, ln
Lnict_inv_share	Share of ICT investments in total investments, ln
Demand and market conditions	
Demand	Assessment of demand development on prime market, average for the period 2009-2014, -2 strong decrease / 2 strong increase
Price	Strong or very strong price competition on prime market, 1 yes / 0 no
Nprice	Strong or very strong non-price competition on prime market, 1 yes / 0 no
N_compet_1	Number of main competitors <=5, 1 yes / 0 no
N_compet_23	Number of main competitors 6 to 15, 1 yes / 0 no
N_compet_4	Number of main competitors 16 to 50, 1 yes / 0 no
Appropriability conditions	
Copy_imped	Innovations can be easily copied, 1 yes / 0 no
Technological opportunities & external knowledge acquistion	
Tech_pot	Technological potential, i.e., technological knowledge which is available worldwide and can be used for the creation of novelties, high or very high, 1 yes / 0 no
Know_comp	Knowledge source competitors used, 1 yes / 0 no
Know_supp	Knowledge source suppliers used, 1 yes / 0 no

Know_cust	Knowledge source customers used, 1yes / 0 no
Know_external	Knowledge source research institutions, universities, consultants, technology transfer or other external sources that are open to general public used, 1 yes / 0 no
Know_comp_int	Knowledge source competitors important or very important, 1 yes / 0 no
Know_supp_int	Knowledge source suppliers important or very important, 1 yes / 0 no
Know_cust_int	Knowledge source customers important or very important, 1 yes / 0 no
Know_external_int	Knowledge source research institutions, universities, consultants, technology transfer or other external sources that are open to general public important or very important, 1 yes / 0 no
Know_breadth	Number of knowledge sources used
Know_depth	Number of knowledge sources that are important or very important
Know_breadth2	know_breadth squared
Know_depth2	know_depth squared
Rnd_coop	R&D cooperation during the last three years, 1 yes / 0 no (dummy variable is 0 for all non-innovators)
Rnd_ext	External R&D, 1 yes / 0 no (dummy variable is 0 for all non-innovators)
Controls	
Lnempl	Number of employees, ln
Lnage	Firm age, ln
Foreign_owned	Firm owned by foreign company
Multinomial variable	
Value 0	Non-innovating, non-performing firms (i.e. firms without sales of innovative products; INNOV=0 & IMIT= 0) in every period
Value 1	'Occasional' innovators or imitators (i.e. INNOV=0 & IMIT=0 → INNOV>0 & IMIT>=0 resp. INNOV=0 & IMIT=0 → INNOV0 & IMIT>0 and the other way around: INNOV>0 & IMIT>=0 → INNOV=0 & IMIT=0 resp. INNOV=0 & IMIT>0 → INNOV=0 & IMIT=0)
Value 2	'Switchers': Imitators that change to innovators (i.e. INNOV=0 & IMIT>0 → INNOV>0 & IMIT>=0); Innovators that change to imitators (i.e. INNOV>0 & IMIT>=0 → INNOV=0 & IMIT>0)
Value 3	'Persistent innovators' or 'persistent imitators' (i.e. INNOV>0 & IMIT>=0 → INNOV>0 & IMIT>=0 resp. INNOV=0 & IMIT>0 → INNOV=0 & IMIT>0.

Table 2: Composition of the sample with respect to different firm categories of innovating and non-innovating firms

Change in the period (t-1, t):	Number of firms	Percentage
Non-innovating in every period	328	33.0
Non-innovating to imitator	27	2.7
Non-innovating to innovator	97	9.8
Imitator to non-innovating	28	2.8
Innovator to non-innovating	88	8.9
Imitator to innovator	52	5.2
Innovator to imitator	44	4.4
Imitator to imitator	15	1.5
Innovator to innovator	315	31.7
Total	*994*	*100*

Table 3: Marginal effects from fractional logit models, IMIT and INNOV, innovators only

	innovators only									
	IMIT	INNOV	IMIT	INNOV	IMIT	INNOV	IMIT	INNOV	IMIT	INNOV
Rnd	0.002	0.039***	0.004	0.041***	0.000	0.041***	0.001	0.042***	0.000	0.041***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lnempl_shr_higher	-0.002	0.009*	-0.002	0.010*	-0.003	0.008	-0.003	0.008	-0.003	0.008
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lnempl_shr_train	0.012*	0.005	0.012**	0.005	0.011*	0.004	0.011*	0.004	0.011*	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Skill_imped	0.014	-0.014	0.014	-0.012	0.011	-0.012	0.012	-0.011	0.012	-0.011
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fin_imped	-0.004	-0.003	-0.005	-0.004	-0.004	-0.004	-0.004	-0.005	-0.003	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lninvest_pc	-0.001	-0.003	-0.001	-0.003	-0.001	-0.004	-0.001	-0.004	-0.001	-0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnict_inv_share	0.013**	0.008*	0.012**	0.009**	0.012**	0.007*	0.013**	0.008*	0.013**	0.008*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Demand	0.007	0.002	0.007	0.002	0.008	0.001	0.008	0.001	0.008	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Price	0.007	0.004	0.006	0.004	0.004	0.001	0.006	0.003	0.004	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Nprice	0.004	0.014*	0.003	0.014*	0.003	0.013*	0.004	0.014*	0.003	0.013*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_1	-0.012	0.005	-0.011	0.007	-0.013	0.004	-0.013	0.004	-0.013	0.004
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_23	0.004	-0.002	0.005	-0.002	0.002	-0.004	0.002	-0.004	0.002	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_4	0.017	-0.005	0.018	-0.004	0.013	-0.005	0.014	-0.005	0.013	-0.005
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Copy_imped	0.000	-0.011	-0.002	-0.008	-0.003	-0.010	0.000	-0.008	-0.003	-0.010
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tech_pot	0.032***	0.009	0.029***	0.009	0.026***	0.008	0.030***	0.01	0.025***	0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rnd_coop	0.021**	-0.001	0.021**	-0.001	0.019**	-0.002	0.021**	0.000	0.019**	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rnd_ext	0.015*	0.006	0.015*	0.007	0.017**	0.005	0.018**	0.006	0.016*	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Know_comp	-0.018	-0.017								
	(0.01)	(0.01)								
Know_supp	0.001	0.005								
	(0.01)	(0.02)								
Know_cust	0.022	0.044***								
	(0.02)	(0.02)								
Know_external	0.008	0.019								
	(0.01)	(0.01)								
Know_comp_int			0.001	-0.01						
			(0.01)	(0.01)						
Know_supp_int			0.019*	0.016						
			(0.01)	(0.01)						

Know_cust_int			0.001	0.007						
			(0.01)	(0.01)						
Know_external_int			0.006	-0.017						
			(0.02)	(0.01)						
Know_breadth					0.012*	0.006	0.014**	0.008		
					(0.01)	(0.01)	(0.01)	(0.01)		
Know_breadth2					-0.001**	0.000	-0.001**	0.000		
					(0.00)	(0.00)	(0.00)	(0.00)		
Know_depth					0.007*	0.006			0.008*	0.007*
					(0.00)	(0.00)			(0.00)	(0.00)
Know_depth2					0.000	0.000			-0.001	-0.001
					(0.00)	(0.00)			(0.00)	(0.00)
Lnempl	-0.004	0.004	-0.005	0.005	-0.004	0.006*	-0.004	0.006*	-0.006*	0.006*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnage	-0.005	-0.018***	-0.004	-0.018***	-0.004	-0.016***	-0.004	-0.017***	-0.004	-0.017***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)
Foreign_owned	0.017	-0.016	0.018*	-0.014	0.020**	-0.016*	0.021**	-0.015	0.019*	-0.016*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Industry dummies					included					
Year dummies					included					
AIC	0.683	0.653	0.683	0.654	0.681	0.648	0.680	0.646	0.680	0.646
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ll	-578.715	-551.573	-578.769	-552.145	-605.158	-573.669	-605.651	-573.954	-605.717	-573.788
N	1823	1823	1823	1823	1906	1906	1906	1906	1906	1906
Correlation real and predicted sales of shares	0.301	0.307	0.305	0.302	0.300	0.301	0.294	0.297	0.294	0.300
Link test										
Sales share hat	1.415	1.310	1.650*	1.185	1.557	1.298	1.541	1.242	1.516	1.318
	0.920	0.949	0.898	0.989	0.921	0.997	0.947	1.025	0.949	1.008
Sales share hat squared	0.144	0.101	0.215	0.068	0.185	0.098	0.181	0.083	0.173	0.104
	0.276	0.251	0.269	0.263	0.274	0.263	0.282	0.270	0.282	0.266

* p<0.10, ** p<0.05, *** p<0.01

cluster robust standard errors in parentheses

Table 4: Multinomial logit models, switcher and persistent innovators

	non-innova-tors base category	INNOV or IMIT from time to time	switcher IMIT <=> INNOV	persistent IMIT or INNOV
Lrnd		1.766***	3.566***	3.357***
		(0.36)	(0.55)	(0.40)
Llnempl_shr_higher		0.099	-0.044	0.009
		(0.11)	(0.19)	(0.15)
Llnempl_shr_train		-0.174	-0.226	0.02
		(0.18)	(0.23)	(0.20)
Lskill_imped		-0.324	-0.085	-0.542
		(0.32)	(0.41)	(0.36)
Lfin_imped		-0.761**	-0.757	-0.809**
		(0.31)	(0.47)	(0.40)
Llninvest_pc		0.177***	0.245*	0.264***
		(0.07)	(0.13)	(0.08)
Llnict_inv_share		0.215*	0.029	0.254*
		(0.12)	(0.20)	(0.15)
Ldemand		-0.163	-0.208	0.193
		(0.15)	(0.25)	(0.19)
Lprice		-0.037	-0.357	-0.137
		(0.22)	(0.35)	(0.27)
Lnprice		0.308	0.198	0.523*
		(0.24)	(0.33)	(0.28)
Ln_compet_1		1.179***	0.899	1.362***
		(0.35)	(0.60)	(0.45)
Ln_compet_23		0.862***	0.729	1.274***
		(0.33)	(0.56)	(0.42)
Ln_compet_4		0.66	0.754	1.137**
		(0.42)	(0.67)	(0.54)
Lcopy_imped		-0.604**	-0.890**	-1.053***
		(0.25)	(0.37)	(0.30)
Ltech_pot		-0.24	0.046	-0.038
		(0.30)	(0.38)	(0.31)
Lknow_breadth		0.300**	0.191	0.167
		(0.13)	(0.26)	(0.20)
Lknow_breadth2		-0.020***	-0.012	-0.009
		(0.01)	(0.01)	(0.01)
Lknow_depth		0.184	0.252	0.101
		(0.12)	(0.17)	(0.14)
Lknow_depth2		-0.011	-0.022	-0.004
		(0.01)	(0.02)	(0.02)
Lrnd_coopi		1.072	1.511**	1.259*
		(0.68)	(0.70)	(0.67)
Lrnd_exti		0.681	1.549***	1.160**

		(0.50)	(0.57)	(0.50)
Llnempl		0.153	0.231	0.278**
		(0.11)	(0.15)	(0.12)
Llnage		0.061	0.327	0.15
		(0.14)	(0.23)	(0.18)
Lforeign_owned		-1.005***	-1.277***	-1.129***
		(0.34)	(0.49)	(0.38)
Industry dummies			included	
Year dummies			included	
Constant		-4.297***	-7.654***	-9.210***
		(1.30)	(2.06)	(1.64)
Pseudo R-squared	0.32			
Prob > chi2	0.00			
ll	-879.591			
N	994			

* p<0.10, ** p<0.05, *** p<0.01

Appendix

Table A.1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Innopd	3294	0.648	0.478	0	1
INNOV	1906	15.157	16.856	0	100
IMIT	1906	13.948	16.073	0	100
Rnd	3294	0.550	0.498	0	1
Lnempl_shr_higher	3294	2.683	0.999	0	4.615
Lnempl_shr_train	3294	3.703	0.697	0	4.615
Skill_imped	3294	0.158	0.364	0	1
Fin_imped	3294	0.123	0.328	0	1
Lninvest_pc	3294	8.893	1.813	0	15.054
Lnict_inv_share	3294	2.423	0.935	0	5.017
Demand	3294	3.274	0.768	1	5
Price	3294	0.704	0.456	0	1
Nprice	3294	0.338	0.473	0	1
N_compet_1	3294	0.341	0.474	0	1
N_compet_23	3294	0.432	0.495	0	1
N_compet_4	3294	0.105	0.307	0	1
Copy_imped	3294	0.200	0.400	0	1
Tech_pot	3294	0.282	0.450	0	1
Rnd_coop	3294	0.221	0.415	0	1
Rnd_ext	3066	0.330	0.470	0	1
Know_comp	3294	0.844	0.363	0	1
Know_supp	3294	0.920	0.271	0	1
Know_cust	3066	0.912	0.283	0	1
Know_external	3294	0.872	0.335	0	1
Know_comp_int	3066	0.259	0.438	0	1
Know_supp_int	3294	0.175	0.380	0	1
Know_cust_int	3294	0.457	0.498	0	1
Know_external_int	3294	0.061	0.240	0	1
Know_breadth	3294	10.102	3.301	0	14
Know_depth	3294	3.071	2.539	0	14
Lnempl	3294	4.157	1.408	0	9.952
Lnage	3294	3.825	0.832	0	6.468
Foreign_owned	3294	0.178	0.383	0	1

Table A.2: Correlation matrix

	Innopd	INNOV	IMIT	Rnd	Lnempl_shr_higher	Lnempl_shr_train	Skill_imped	Fin_imped	Lninvest_pc	Lnict_inv_share	Demand	Price	Nprice	N_compet_1	N_compet_23	N_compet_4	Copy_imped	Tech_pot	Rnd_coop	Rnd_ext
Innopd	1.000																			
INNOV	0.152	1.000																		
IMIT	0.171	0.087	1.000																	
Rnd	0.232	0.063	0.142	1.000																
Lnempl_shr_higher	0.075	0.036	0.115	0.200	1.000															
Lnempl_shr_train	-0.004	0.001	-0.020	-0.052	-0.187	1.000														
Skill_imped	0.023	0.054	-0.006	0.029	0.040	-0.044	1.000													
Fin_imped	-0.048	0.006	-0.013	0.005	0.003	-0.038	0.116	1.000												
Lninvest_pc	-0.017	-0.040	-0.071	-0.001	-0.028	0.046	-0.006	-0.059	1.000											
Lnict_inv_share	0.037	0.084	0.081	0.010	0.118	0.028	-0.015	-0.017	-0.095	1.000										
Demand	0.084	0.066	0.054	0.118	0.086	0.008	0.002	-0.087	0.099	-0.006	1.000									
Price	-0.010	0.006	-0.004	0.034	-0.011	0.036	0.033	0.018	-0.010	0.004	-0.137	1.000								
Nprice	0.014	0.053	0.068	0.063	0.058	0.011	0.019	-0.013	0.042	0.012	0.072	-0.103	1.000							
N_compet_1	0.046	-0.037	0.041	0.042	0.070	-0.051	-0.056	-0.053	0.033	0.022	0.034	-0.138	0.017	1.000						
N_compet_23	0.008	0.024	-0.010	0.026	-0.012	-0.011	0.028	-0.041	-0.044	0.018	0.000	0.091	-0.044	-0.673	1.000					
N_compet_4	0.001	0.040	-0.024	-0.067	-0.024	0.035	0.015	0.052	0.000	-0.034	-0.008	0.051	0.029	-0.250	-0.299	1.000				
Copy_imped	0.037	-0.006	-0.035	0.067	-0.024	-0.011	0.115	0.114	-0.026	-0.017	-0.059	0.093	-0.009	-0.080	0.034	0.028	1.000			
Tech_pot	0.063	0.122	0.073	0.114	0.141	-0.052	0.088	0.026	0.053	0.095	0.111	0.040	0.121	0.000	-0.001	0.002	-0.011	1.000		
Rnd_coop	0.110	0.094	0.078	0.337	0.206	-0.037	0.019	0.041	0.052	0.028	0.079	0.003	0.090	0.042	-0.011	-0.007	-0.013	0.173	1.000	
Rnd_ext	0.147	0.087	0.107	0.486	0.224	-0.018	0.029	-0.034	0.052	0.037	0.107	0.043	0.061	0.087	-0.020	-0.064	0.028	0.179	0.356	1.000
Know_comp	0.058	-0.037	-0.014	0.016	0.106	0.003	0.009	-0.010	0.032	-0.004	0.038	0.047	0.052	-0.043	0.051	-0.011	0.054	0.056	-0.010	0.057
Know_supp	-0.026	0.017	0.023	0.021	-0.003	0.062	0.033	0.006	0.010	-0.001	0.024	0.096	0.009	-0.032	-0.008	0.038	0.057	0.060	0.034	0.053
Know_cust	0.122	0.045	0.092	0.107	0.078	-0.011	0.043	-0.042	-0.027	0.047	0.016	0.054	-0.029	-0.001	0.003	0.007	0.072	-0.006	0.020	0.092
Know_external	0.051	0.046	0.074	0.207	0.146	0.025	0.091	0.043	0.044	0.067	0.099	0.059	0.069	-0.016	0.037	-0.032	0.051	0.162	0.142	0.220
Know_comp_int	-0.023	0.013	-0.018	0.016	0.073	0.023	0.046	-0.021	0.038	-0.006	0.031	0.100	0.067	-0.009	0.017	0.025	0.091	0.111	0.021	0.056
Know_supp_int	-0.060	0.054	0.023	-0.001	-0.059	0.011	0.045	0.049	0.031	0.060	-0.017	0.078	0.010	-0.026	-0.022	0.023	0.069	0.138	0.024	0.040
Know_cust_int	0.043	0.036	0.059	0.093	0.082	-0.011	0.070	-0.013	0.018	0.025	0.060	0.089	0.064	-0.012	0.040	-0.008	0.069	0.130	0.068	0.080
Know_external_int	0.040	0.033	0.006	0.078	0.126	-0.031	0.033	-0.001	0.060	0.009	0.068	0.059	0.056	0.059	-0.034	-0.005	0.067	0.227	0.122	0.128
Know_breadth	0.110	0.036	0.083	0.236	0.230	0.032	0.064	-0.025	0.079	0.064	0.120	0.088	0.055	0.036	0.004	-0.023	0.058	0.233	0.180	0.326
Know_depth	0.065	0.086	0.077	0.169	0.153	-0.004	0.103	0.012	0.073	0.067	0.088	0.123	0.120	0.012	-0.009	0.023	0.150	0.335	0.211	0.249
Lnempl	0.050	-0.011	0.038	0.175	0.184	0.019	-0.048	-0.154	0.180	0.014	0.104	0.074	0.082	0.074	0.011	-0.031	-0.103	0.129	0.213	0.256
Lnage	-0.042	-0.054	-0.115	0.003	-0.082	0.023	-0.058	-0.050	0.099	-0.020	-0.070	0.067	0.007	0.000	0.004	0.004	0.005	-0.077	0.016	0.015
Foreign_owned	0.019	0.059	0.029	0.072	0.153	-0.037	0.015	-0.091	-0.035	0.019	0.100	0.017	0.023	0.085	-0.003	-0.045	-0.063	0.104	0.023	0.107

continued

	Know_ comp	Know_ supp	Know_ cust	Know_ external	Know_ comp _int	Know_ supp_ int	Know_ cust_ int	Know_ exter-nal_ int	Know_ breadth	Know_ depth	Lnempl	Lnage	Foreign_owned
Know_comp	1.000												
Know_supp	0.107	1.000											
Know_cust	0.182	0.153	1.000										
Know_external	0.217	0.206	0.145	1.000									
Know_comp_int	0.278	0.094	0.072	0.142	1.000								
Know_supp_int	0.064	0.127	0.019	0.108	0.074	1.000							
Know_cust_int	0.142	0.154	0.290	0.160	0.194	0.043	1.000						
Know_external_int	0.091	0.076	0.041	0.103	0.188	0.138	0.118	1.000					
Know_breadth	0.447	0.404	0.338	0.599	0.226	0.179	0.241	0.289	1.000				
Know_depth	0.224	0.235	0.176	0.343	0.470	0.420	0.441	0.539	0.519	1.000			
Lnempl	0.159	0.102	0.100	0.184	0.109	0.011	0.104	0.211	0.376	0.209	1.000		
Lnage	-0.001	0.028	-0.002	0.046	-0.001	0.020	0.005	0.014	0.035	0.005	0.199	1.000	
Foreign_owned	0.032	0.014	0.081	0.074	0.051	-0.044	0.102	0.061	0.158	0.129	0.161	-0.112	1.000

Table A.3: Marginal effects from logit models, innopd

	Innopd	Innopd	Innopd	Innopd	Innopd
Rnd	0.362***	0.358***	0.363***	0.363***	0.368***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lnempl_shr_higher	0.002	0	0.005	0.005	0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lnempl_shr_train	0.006	0.007	0.012	0.011	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Skill_imped	-0.002	-0.001	0	-0.001	0
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Fin_imped	-0.030*	-0.030*	-0.025	-0.027	-0.027
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Lninvest_pc	0.009***	0.009***	0.010***	0.010***	0.009***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnict_inv_share	0.022***	0.024***	0.023***	0.023***	0.023***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Demand	0.012	0.011	0.008	0.008	0.007
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Price	0.02	0.021	0.012	0.01	0.011
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Nprice	0.019	0.02	0.022*	0.021	0.023*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_1	0.063***	0.062***	0.058***	0.057***	0.061***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N_compet_23	0.042**	0.042**	0.049***	0.049***	0.050***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N_compet_4	0.050**	0.050**	0.066***	0.065***	0.066***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Copy_imped	-0.007	-0.003	-0.002	-0.004	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tech_pot	0.022	0.028*	0.024	0.022	0.024
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Rnd_coop	0.033	0.031	0.037	0.036	0.038
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Rnd_ext	0.052*	0.054**	0.070**	0.070**	0.062**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Know_comp	0.014				
	(0.02)				
Know_supp	-0.016				
	(0.02)				
Know_cust	0.032				
	(0.02)				
Know_external	-0.033**				
	(0.02)				
Know_comp_int		-0.031**			
		(0.01)			
Know_supp_int		-0.046***			
		(0.02)			
Know_cust_int		0.003			
		(0.01)			

Know_external_int		0.022			
		(0.03)			
Know_breadth			0.019**	0.015*	
			(0.01)	(0.01)	
Know_breadth2			-0.001***	-0.001***	
			(0.00)	(0.00)	
Know_depth			-0.012*		-0.012*
			(0.01)		(0.01)
Know_depth2			0.001		0.001
			(0.00)		(0.00)
Lnempl	0.011**	0.012**	0.017***	0.017***	0.014***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnage	-0.002	-0.003	0	0	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Foreign_owned	-0.043**	-0.043**	-0.027	-0.027	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Industry dummies			included		
Year dummies			included		
Pseudo R-squared	0.5038	0.427	0.418	0.501	0.497
Prob > chi2	0.000	0.000	0.000	0.000	0.000
Ll	-971.347	-968.288	-1065.061	-1066.666	-1075.821
N	3066	3066	3294	3294	3294
Sensitivity (%)	84.52	84.52	83.69	83.69	83.04
Specificity (%)	91.37	91.37	92.41	92.07	92.50
Correctly classified (%)	86.82	86.82	86.76	86.64	86.37
Correlation predicted and real innovation dummy	0.752	0.753	0.754	0.753	0.75
Link test					
Innovation dummy hat	1.006***	1.012***	1.071***	1.063***	1.044***
	0.054	0.053	0.052	0.052	0.054
Innovation dummy hat squared	-0.003	-0.006	-0.038*	-0.033	-0.023
	0.022	0.022	0.021	0.021	0.022

* p<0.10, ** p<0.05, *** p<0.01

cluster robust standard errors in parentheses

Table A.4: Marginal effects from fractional logit models, IMIT and INNOV, whole sample

	whole sample									
	INNOV	IMIT	INNOV	IMIT	INNOV	IMIT	INNOV	IMIT	INNOV	IMIT
Rnd	0.111***	0.125***	0.112***	0.126***	0.106***	0.122***	0.106***	0.122***	0.108***	0.123***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lnempl_shr_higher	0.000	0.007**	0.000	0.008**	0.001	0.007**	0.001	0.007**	0.000	0.007**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnempl_shr_train	0.008*	0.003	0.009**	0.004	0.009**	0.004	0.008**	0.004	0.008**	0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Skill_imped	0.009	-0.008	0.01	-0.007	0.008	-0.007	0.009	-0.006	0.009	-0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fin_imped	-0.005	-0.005	-0.006	-0.005	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lninvest_pc	0.002	-0.001	0.002	0.000	0.002	-0.001	0.002	-0.001	0.002	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnict_inv_share	0.011***	0.008***	0.011***	0.008***	0.011***	0.007**	0.011***	0.007***	0.011***	0.007**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Demand	0.006	0.003	0.006	0.003	0.006	0.002	0.006	0.002	0.006	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Price	0.006	0.004	0.005	0.004	0.003	0.001	0.004	0.002	0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Nprice	0.006	0.012**	0.005	0.012**	0.005	0.011**	0.006	0.012**	0.006	0.012**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_1	0.004	0.01	0.004	0.011	0.004	0.01	0.004	0.01	0.004	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_23	0.014	0.005	0.014	0.005	0.013	0.006	0.014	0.006	0.014	0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N_compet_4	0.023**	0.002	0.024**	0.004	0.022**	0.005	0.023**	0.005	0.023**	0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Copy_imped	-0.004	-0.010*	-0.005	-0.008	-0.006	-0.009	-0.004	-0.008	-0.006	-0.009
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tech_pot	0.023***	0.006	0.021***	0.006	0.019***	0.005	0.021***	0.007	0.018***	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rnd_coop	0.013**	-0.002	0.013**	-0.002	0.011*	-0.002	0.012**	-0.001	0.012**	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Rnd_ext	0.011*	0.005	0.011*	0.006	0.013**	0.005	0.014**	0.006	0.012**	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Know_comp	-0.013*	-0.011								
	(0.01)	(0.01)								
Know_supp	0.002	0.002								
	(0.01)	(0.01)								
Know_cust	0.015	0.032***								
	(0.01)	(0.01)								
Know_external_int	-0.002	0.008								
	(0.01)	(0.01)								
Know_comp_int			-0.004	-0.010*						
			(0.01)	(0.01)						
Know_supp_int			0.009	0.008						
			(0.01)	(0.01)						

Know_cust_int			-0.001	0.003						
			(0.01)	(0.01)						
Know_external_int			0.004	-0.011						
			(0.01)	(0.01)						
Know_breadth					0.009**	0.006	0.010**	0.007*		
					(0.00)	(0.00)	(0.00)	(0.00)		
Know_breadth2					-0.001***	-0.000*	-0.001***	-0.000*		
					(0.00)	(0.00)	(0.00)	(0.00)		
Know_depth					0.004	0.003			0.003	0.003
					(0.00)	(0.00)			(0.00)	(0.00)
Know_depth2					0.000	0.000			0.000	0.000
					(0.00)	(0.00)			(0.00)	(0.00)
Lnempl	-0.002	0.004*	-0.002	0.005**	-0.001	0.006***	-0.001	0.006***	-0.002	0.005**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lnage	-0.004	-0.013***	-0.004	-0.013***	-0.003	-0.011***	-0.003	-0.011***	-0.003	-0.011***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Foreign_owned	0.008	-0.014**	0.009	-0.013*	0.011	-0.013**	0.011*	-0.012*	0.01	-0.013**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Industry dummies					included					
Year dummies					included					
AIC	0.491	0.461	0.492	0.461	0.480	0.447	0.479	0.446	0.480	0.446
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Ll	-634.783	-592.916	-635.025	-593.397	-669.189	-620.160	-669.621	-620.379	-670.727	-620.634
N	2763	2763	2763	2763	2972	2972	2972	2972	2972	2972
Correlation real and predicted sales of shares	0.458	0.486	0.459	0.484	0.459	0.487	0.457	0.486	0.457	0.488
Link test										
Sales share hat	0.744	0.651	0.806*	0.610	0.647	0.555	0.596	0.517	0.763	0.638
	0.467	0.469	0.466	0.472	0.447	0.463	0.453	0.468	0.466	0.469
Sales share hat squared	-0.055	-0.071	-0.042	-0.079	-0.076	-0.090	-0.087	-0.097	-0.051	-0.073
	0.099	0.094	0.099	0.095	0.095	0.092	0.097	0.093	0.098	0.093

* p<0.10, ** p<0.05, *** p<0.01

cluster robust standard errors in parentheses