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When 'national innovation system' meet 'varieties of capitalism' arguments on labour qualifications: On the skill types and scientific knowledge needed for radical and incremental product innovations

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ABSTRACT

The literatures on 'varieties of capitalism' (VoC) and 'national innovation systems' (NIS) propose very similar arguments about how firms require different types of labour qualifications to pursue strategies of radical product innovation (RPI), incremental product innovation (IPI), and product imitation (PI) respectively. Despite their similar lines of reasoning, however, the VoC scholars are concerned with the skill profiles of a firm's entire workforce, whereas the NIS proponents focus on the knowledge base of scientists. Given that both literatures have developed without explicitly taking the arguments of the neighbouring discipline into account, it is thus unclear whether they explain the same, or different, phenomena. Furthermore, both literatures propose firm level arguments but test them on the basis of macro- rather than micro-level indicators. This paper therefore asks: first, does micro-level evidence support the VoC and NIS arguments that particular types of employee skills and knowledge backgrounds of scientists are needed for different competitive strategies? And, if so, do RPI, IPI, and PI firms need to employ scientists *in combination with* a workforce having the respective qualifications, or is it sufficient if scientists *or* employees alone are adequately qualified. Quantitative analyses indicate that a particular mix of scientific knowledge *combined with* employee skills facilitate RPI, IPI, and PI strategies. The article thus concludes that – despite their similar reasoning – the VoC and the NIS literatures indeed describe different phenomena, without being aware of the synergies created whenever adequate employee and scientific qualifications are hired together.

1. Introduction: two different literatures, one similar argument

Agreement is broad amongst contributors to the competitiveness literature that firms require people with distinct qualifications in order to pursue different product-market strategies. While employees with 'general' or 'multi-tasking' skills are said to be needed for radical product innovation, workers with 'firm-specific' or 'occupational specialization' skills presumably facilitate incremental product innovation. Low qualified and, hence, inexpensive labour is claimed to be required for low cost production based on product imitation.[3]

Despite this general agreement, different strands of the competitiveness literature focus on diverse *holders* of qualifications. While the literature on 'varieties of capitalism' (VoC) proposes arguments about the qualifications of the *overall labour force* of a company,[4] the literature on 'national innovation systems' (NIS) tends to focus on the knowledge base of a *firm's scientists*.[5] More concretely, the VoC literature argues that radical product innovation (RPI) requires *employees* with general skills because they can

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[3] See Porter (1990): 73–76, Freeman and Soete (1997a); Hollingsworth (2000): 626–630, Estevez-Abe et al. (2001), Hall and Soskice (2001a): 36–44, Lindbeck and Snower (2001), Amable (2003), Casper and Whitley (2004), Casper (2007), see also Freeman (1992), Patel and Pavitt (1994): 89–92, Hage and Hollingsworth (2000), Hollingsworth and Hollingsworth (2000), Nooteboom et al. (2007).

[4] See Estevez-Abe et al. (2001), Hall and Soskice (2001a), Iversen and Soskice (2001), Amable (2003), Casper and Whitley (2004), and Casper (2007).

[5] See Freeman and Soete (1997a), Hollingsworth (2000): 626–630, Hollingsworth and Hollingsworth (2000), see also Freeman (1992), Patel and Pavitt (1994): 89–92, and Hage and Hollingsworth (2000).

adapt more easily to constantly changing supplier–producer relationships and market demands which, in turn, are characteristic of this product-market strategy. Specific skills are said to be necessary for incremental product innovation (IPI) because the in-depth knowledge of a company, of its market, its suppliers and customers enables employees to continuously improve products and production processes, and to adopt products to specific customer needs. Furthermore, employees with an in-depth understanding of how their firm operates are able to work autonomously and to take on responsibility. They know, for example, how to rectify mistakes that occur during the production process, which, in turn, contributes to maintaining a high level of product quality. Finally, product imitation (PI) is said to rely on employees with neither general nor specific but with low skills as their salary levels are reduced. Even though low-skilled employees cannot often rectify mistakes that occur during the production process without precise instructions from their superiors, this does not harm the pursuit of PI strategies, as product quality is less important than product costs.[6]

The NIS literature, on the other hand, illustrates how the employment of *scientists* with diverse knowledge backgrounds crucially enables to pursue RPI, IPI, and PI strategies. Scientists with heterogeneous knowledge are said to facilitate RPI as 'it might take an enormous intellectual effort or an extremely creative mind, to identify a potential new combination' (Lundvall, 1992b: 8; see also Johnson, 1992: 29). Scientists who have worked with colleagues from diverse universities, countries, and disciplines – while being rather autonomous from their supervising professor – are more likely to have the necessary, radically innovative potential due to their increased imaginative capacities. Scientists with a homogeneous knowledge base, on the contrary, are found to enable the pursuit of IPI strategies. Since they have worked within the same field of research and the same team for a long time, scientists with homogeneous knowledge have an in-depth understanding of the technological opportunities in this area and are used to cooperating, and to combining their insights, in order to develop incremental innovations. At the same time, they might be so familiar with one environment that they have difficulties to imagine entirely new realities and, thus, lack the creative capacities to come up with radically new ideas. Finally, PI firms do neither require scientists with a heterogeneous nor a homogeneous knowledge base as they imitate the inventions of their competitors. PI strategists thus benefit from not hiring scientists.[7]

Two features of these literatures are particularly noteworthy. First, both literatures do not test their arguments on the basis of micro-, that is, firm-level indicators. Instead, the NIS and VoC literatures start from the observation that the innovative performance and product market strategies of firms vary between countries and seem to be supported by national institutions, including research as well as education and training (E&T) systems. Based on data aggregated at the industry level, both literatures conclude that these institutional differences cause firms to embark on diverse innovation or product market strategies as they facilitate the availability of different factor types, including scientific knowledge and employee skills. With some very few exceptions,[8] micro-level assessments of scientific knowledge and skill profiles are not provided.[9]

Second, even though they both propose similar lines of reasoning, it is unclear whether the NIS and the VoC arguments refer to the same or different phenomena, because the two literatures developed in parallel without explicitly taking the arguments of the neighbouring discipline into account. While the VoC scholars consider the education and training which *employees* receive,[10] the NIS proponents are rather concerned with the career paths of *scientists*.[11] Ultimately, though, the reasoning of both literatures rests on the insight that the increased exposure of people to new ideas – be it in the form of employees changing firms more regularly, be it in the form of scientists being more autonomous and performance oriented in their choice of research projects – is crucial for the emergence of radical innovations. But, do firms need to hire scientists with a particular knowledge profile *in addition to* a workforce with distinct qualifications in order to pursue RPI, IPI, and PI strategies respectively? Or is it sufficient if scientists alone have a particular knowledge base, given that they constitute that employment group with the key capacities for innovation? Or are scientists merely one group of the firm's entire workforces and, hence, require particular skill profiles rather than knowledge backgrounds?

Consequently, this article has two aims. First, it analyses whether micro-level data confirms the NIS and VoC arguments on the importance of different qualification types for RPI, IPI, and PI strategies. Second, the article explores whether the VoC and the NIS literatures explain similar or different phenomena. To these ends, the article studies pharmaceutical firms – including biotech, traditional pharmaceutical, and generics firms – in Germany, Italy, and the UK. *Pharmaceutical* firms are particularly revealing cases to study as the scientifically established notion of a 'new chemical entity' allows the distinction between RPI, IPI, and PI strategies at the firm level.

Furthermore, firms in *different countries* need to be studied so as to reveal whether possible differences in the labour qualifications employed by RPI, IPI, and PI firms result from the competitive strategies of these firms, or from the sheer availability of diverse qualifications due to the country's research and E&T systems. If the employee skills and scientific knowledge employed by RPI, IPI, and PI firms differ between these competitive strategies rather than between countries, we can conclude that firms cannot randomly hire people, but that RPI, IPI, and PI strategies require workforces with distinct qualification profiles. *Germany*, *Italy*, and *the UK* offer most comprehensive insights as these countries are said to have particularly characteristic E&T and research systems providing people with the required qualifications for RPI, IPI, and PI strategies. More precisely, the E&T and research systems of the UK are held to teach employees and scientists mostly qualifications which are required for RPI strategies, whereas Germany's E&T and research systems are found to provide people with the necessary qualifications for IPI strategies. The poorly developed E&T and research systems of Italy, in turn, are said to leave people with neither general nor specific and, hence, low skills, thereby facilitating the pursuit of PI strategies.[12]

[6] See Estevez-Abe et al. (2001): in particular 173-176, Hall and Soskice (2001a): 21–33, 36–44, Casper and Whitley (2004), see also Iversen and Soskice (2001), and Amable (2003).

[7] See Freeman and Soete (1997a): in particular 268–281, Hollingsworth (2000): 626–630, Nooteboom et al. (2007), see also Hollingsworth and Hollingsworth (2000).

[8] See, for example, Hollingsworth and Hollingsworth (2000), Iversen and Soskice (2001), and Nooteboom et al. (2007).

[9] See, for example, Freeman and Soete (1997a), Hage and Hollingsworth (2000), Hollingsworth (2000), Estevez-Abe et al. (2001), Hall and Soskice (2001a), Amable (2003), Casper and Whitley (2004), see also Patel and Pavitt (1994).

[10] See footnote 4.

[11] See footnote 5.

[12] For proponents of these arguments (Keck, 1993; Malerba, 1993; Walker, 1993; Estevez-Abe et al., 2001; Hall and Soskice, 2001a; Amable, 2003; Casper and Whitley, 2004, see also Patel and Pavitt, 1994; Freeman and Soete, 1997b).

To understand whether micro-level data confirms the VoC and NIS reasoning and to illustrate whether these literatures propose similar or different arguments, the article proceeds as follows. Section 2 uses micro-level indicators in order to identify firms that pursue RPI, IPI, and PI strategies in the UK, Germany, and Italy. Section 3 conceptualizes, operationalizes, and measures the *skill types of employees* who work for the RPI, IPI, and PI firms identified in Section 2. Analyzing interviews with the firms' Human Resources managers, Section 3 furthermore presents the results of multinomial logistic regressions which show that RPI, IPI, and PI strategists indeed rely on employees with general, specific, and low skills respectively. Similarly, Section 4 conceptualizes, operationalizes, and measures the knowledge base of *scientists* working for these firms and illustrates with the help of binary logistic regressions that RPI and IPI strategies employ scientists with heterogeneous and homogenous knowledge respectively, whereas PI firms do typically not require scientific knowledge. Section 5 finally sheds light on the question whether firms need particular employee skills in addition to distinct scientific knowledge. Interestingly, binary logistic regressions not only show this to be the case, but also suggest that synergy effects are created whenever adequate employee and scientific qualifications are hired together. Section 6 therefore concludes that, despite their similar reasoning, the VoC and NIS arguments describe different empirical phenomena without realizing the competitiveness-enhancing potential of their combined reasoning.

2. The sample: identifying firms that pursue RPI, IPI, and PI strategies

It is first necessary to identify the competitive strategies of firms in order to assess then upon which employee skills and scientific qualifications firms rely. Following the standard definitions of the competitiveness literature, a competitive strategy is here conceptualized as a process that leads to the emergence of a good which, in turn, gives the producing firm a sustainable advantage on the market.[13] Three ways are identified in the literature through which firms can obtain a sustainable advantage. First, a firm can develop completely new goods and, hence, pursue a strategy of radical product innovation (RPI). Second, a firm can develop already existing products that are of a superior quality than those of its competitors. In this way, the firm gains a sustainable advantage through incremental product innovation (IPI). Third, a firm can develop existing goods that are cheaper than competing products, thereby pursuing a strategy of product imitation (PI). In short, a sustainable advantage results either from developing radically new, incrementally new, or cheaper goods. While RPI strategies are based on the development of radically new technologies, IPI strategies rely on incrementally new technologies, whereas PI strategies are based on the imitation of technologies.

Due to two systematic differences in their technological intensity, pharmaceutical firms[14] offer particularly suitable cases to operationalize these conceptual distinctions. First, RPI, IPI, and PI strategists can be discerned due to the scientifically acknowledged concept of a 'new chemical entity' (NCE), i.e. a previously unknown molecular structure. Whenever pharmaceutical firms develop a therapeutic product, they indicate whether their drug is based on an NCE, the improvement of an already discovered chemical entity, or an imitation thereof. Competitive strategies can thus be discerned as follows. Pharmaceutical firms that primarily develop drugs on the basis of NCEs pursue RPI strategies, while firms are IPI strategists whenever they develop drugs based on improved molecular structures. Pharmaceutical firms that abstain from R&D activities and produce drugs based on imitations of molecular structures pursue PI strategies. Importantly, however, firms find it inherently difficult to develop drugs exclusively on the basis of NCEs, because the discovery of pharmaceutically useful NCEs is in large part unpredictable and, hence, rare. While it is partly beyond the control of pharmaceutical firms to discover pharmaceutically useful NCEs, firms can decide to be radically innovative by focusing on up-stream activities of the value chain.

Consequently, the value-chain focus of pharmaceutical firms constitutes a second indicator that enables the identification of RPI, IPI, and PI strategies. Due to the high risks and costs involved, new therapeutics are typically not developed by one single drug firm but rather by two or more cooperation partners in a row (see Gambardella et al., 2001: 36–53). While biotech firms often focus on up-stream activities of discovery and preclinical development, traditional pharmaceutical firms tend to specialize in mid-stream activities of clinical development and pharmaceutical production.[15] Generics firms abstain from R&D activities and focus on down-stream processes of production, registration, marketing and sales. While this division of labour is not always clear-cut, because some biotech firms specialize in mid-stream activities, while some traditional pharmaceutical firms focus on up-stream activities of the value chain, it offers a second indicator to distinguish RPI, IPI, and PI strategies: Pharmaceutical firms that specialize in up-stream activities of the value chain seek to be radically innovative, while their counterparts focusing on mid-stream activities aim at incremental innovations, whereas companies that are active in down-stream activities are typically drug imitators.

Together, the value-chain focus of a pharmaceutical firm and the molecular structure of its drugs make it possible to identify its competitive strategies according to the following criteria.

- A pharmaceutical firm pursues an RPI strategy whenever it has discovered at least one NCE over a certain time span, which it either developed into a marketable product on its own, or which it out-licensed to drug developers. Alternatively, pharmaceutical firms can be identified as RPI strategists whenever they focus on up-stream value-chain activities of discovery and preclinical development in the field of biotechnology.
- In contrast, a pharmaceutical firm can be said to pursue an IPI strategy whenever it has not discovered an NCE but developed at least one drug on the basis of an improved chemical entity over a certain time span – either on its own or in cooperation with others. In doing so, the pharmaceutical firm in question is incrementally innovative as it focuses on mid-stream value-chain activities of clinical development and pharmaceutical production whereby it typically applies traditional pharmaceutical methods.
- Finally, a pharmaceutical firm can be said to pursue a PI strategy if it abstains from R&D activities and imitates pharmaceutical

[13] See Porter (1980): chapter 2, see also Porter (1985): chapter 1, Lundvall (1992b): 10, Casper, 2001: 397–401, Estevez-Abe et al. (2001): 148–149, Hall and Soskice (2001a): 14–17.

[14] It should be noted that a *pharmaceutical firm* is here used as an overarching term for any drug company discovering, developing or producing therapeutic products. Consequently, pharmaceutical firms include biotechnology, traditional pharmaceutical, and generics firms which differ from each other in their technological approaches. *Biotechnology firms* use the most advanced technologies for drug development as they seek to create industrially useful substances through modifications of a cell or sub-cell. Even though *traditional pharmaceutical firms* sometimes employ biotechnological approaches as well, they mostly develop new pharmaceutical substances through systematic screening rather than deliberate design. *Generics firms*, in turn, use least technology-intense methods as they imitate drugs upon expiry of their patent protection without engaging in biotechnological or traditional R&D activities themselves (Drews and Jürgen, 2000; Orsenigo et al., 2001; Pammolli et al., 2002; Muffatto and Giardian, 2003; Wittner, 2003).

[15] See Bottazzi (2001), Orsenigo et al. (2001), Owen-Smith et al. (2002), and Pammolli et al. (2002).

Table 1
Summary results: RPI, IPI, and PI strategists in the UK, Germany, and Italy.

	Radical product innovators		Incremental product innovators		Product imitators		Total	
	No. firms	% firms	No. firms	% firms	No. firms	% firms	No. firms	% firms
UK	19	47.5%	17	42.5%	4	10.0%	40	39.2%
Germany	13	39.4%	17	51.5%	3	9.1%	33	32.4%
Italy	10	34.5%	11	37.9%	8	27.6%	29	28.4%
Total	42		45		15		102	100.0%
Average	14	41.2%	15	44.1%	5	14.7%	34	

Source: PHID database, sampled in November 2004.

products of competitors. Alternatively, a firm is identified as a PI strategist if it focuses on down-stream value-chain activities of pharmaceutical registration, marketing and sales.

The 'Pharmaceutical Industry Database' (PHID) provides the most complete dataset for identifying competitive strategies according to these criteria.[16] It keeps track of 16,751 pharmaceutical projects carried out by 3522 firms and public research organizations in 7 countries.[17] The latter include Germany, Italy, and the UK, in addition to France, Japan, Switzerland, and the USA.[18] In these countries, any firm is recorded as soon as it has been involved in at least one pharmaceutical project which has reached the stage of preclinical development since the 1980s. Pharmaceutical firms are therefore also included in the PHID database if their projects are not patent protected. Furthermore, only those firms are considered whose projects translated into therapeutic drugs that cure human diseases or alleviate suffering. Platform-technology firms providing R&D services to pharmaceutical companies are not included in the database.

To identify the competitive strategies of pharmaceutical firms in Germany, Italy, and the UK, the PHID database was sampled according to the aforementioned criteria, whereby the sample was limited to those firms that developed at least one pharmaceutical project between 1985 and 2004.[19] The sample obtained is summarized in Table 1.

A detailed list of those firms that qualified as RPI, IPI, and PI strategists in the UK, Germany, and Italy is provided in the technical appendix (see Tables A.1–A.3).[20] These firms serve as the empirical basis for all following analyses.

To better understand these results in view of the existing literature and, hence, the operationalization of competitive strategies proposed here, remember how the seminal studies of Abernathy and Utterback (Utterback, 1994) demonstrate that new industries typically develop out of a critical mass of companies bringing radically innovative products to the market. In other words, firms active in high-tech industries are often radically innovative. This insight has led the broad majority of VoC scholars to measure competitive strategies through the industries in which firms are active (see, for example, Vitols, 2001; Casper and Matraves, 2003; Casper, 2007): Firms active in the biotech industry are said to pursue RPI strategies, whereas traditional pharmaceutical companies are held to pursue IPI strategies, while generics producers are assumed to be PI strategists. The idea that competitive strategies can be measured both via the technological intensity of a *firm's industry*, as proposed by the VoC scholars, as well as via the technological intensity of a *firm's products*, as proposed here, is empirically supported: Factor analyses show that a firm's product focus and its industry load on the same dimension (Alpha Cronbach = .872) – which also speaks for the reliability of the data used here. Importantly, however, it has been demonstrated (Herrmann, 2010) that a firm's industry is the cruder measure of its competitive strategy than its product focus. Whenever the industry is taken as a strategy indicator this implies that all firms within the same industry are assumed to pursue the same competitive strategy. Consequently, biotech firms producing incrementally new goods or traditional pharmaceutical companies developing radically new products are, for example, assigned the 'wrong' strategy. To avoid such misclassifications, the competitive strategy of firms is measured here by the technological intensity of their products rather than their industry.

The informed reader will realize that the sampling results presented in Table 1 are noteworthy by themselves as they indicate that the plurality of firms in Germany, Italy, and the UK alike pursue strategies that are not supported by national institutions. This raises the question how firms can so numerously compete despite comparative institutional disadvantages. Since an in-depth answer to this question has already been provided (Herrmann, 2008), this article pursues new avenues of research. Acknowledging that firms can circumvent national institutions, the article assesses whether the NIS and VoC literatures ultimately describe the same phenomenon when illustrating how firms employ distinct types of labour qualifications to pursue RPI, IPI, and PI strategies.

3. The VoC reasoning: how employees with different skill types facilitate RPI, IPI, and PI strategies

Consequently, the question arises which types of labour qualifications are employed by those RPI, IPI, and PI firms whose competitive strategy was identified in Section 2. To test whether, and if so which, *combination* of employee skills and scientific knowledge is required, it is first necessary to test *separately* whether RPI, IPI, and PI strategists rely on particular types of employee skills on the one hand, and scientists' knowledge on the other. Should micro-level evidence reveal that each of these strategies can be pursued without employees *or* scientists possessing distinct qualifications, it is unnecessary to enquire further about possible combinations of employee and scientist profiles.

Section 3 focuses on the first labour group and investigates the VoC argument claiming that particular types of employee skills are necessary for RPI, IPI, and PI strategies. As illustrated in Section 1, the VoC scholars hypothesize that RPI strategists rely on employees with general skills, because the latter can adapt more easily to new innovation challenges and to constantly changing supplier–producer relationships and market demands. IPI strate-

[16] The PHID database is constantly updated. All figures reported in the following refer to November 2004.

[17] The PHID database identifies the nationality of a firm according to the location of the firm's headquarters.

[18] To be precise, the PHID database covers 67 countries. However, the number of pharmaceutical projects registered in the remaining 60 countries is too limited to provide representative results.

[19] Given that it takes on average 14 years to develop a pharmaceutical product (Muffatto and Giardian, 2003: 108–109), the sample was limited to 20 years in order to cover a sufficiently long time span while eliminating outdated results.

[20] Each of those nine, international pharmaceutical firms which were found to pursue – in two separate business units – an RPI strategy on the one hand and a IPI strategy on the other, are counted as two individual cases. For a more detailed illustration of the sampling approach underlying the results reported in Table 1, see (Herrmann, 2008: chapter 2).

gies, in contrast, are said to rely on employees with specific skills, enabling workers to perform complex assembly tasks, as well as to use and maintain sophisticated, often company-specific machines. Furthermore, specific skills are necessary because an in-depth knowledge of how a firm operates – of its markets, suppliers, and customers – enables employees to continuously improve production processes and to adopt products to specific customer needs. Such firm-specific knowledge also allows employees to work autonomously and to assume responsibility. For example, workers can autonomously rectify mistakes occurring during the production process which, in turn, contributes to maintaining a high level of product quality. Finally, employees with neither general nor specific but low skills are said to facilitate product imitation as their salary levels are reduced. Even though employees with low-level skills are usually less autonomous in their work and can, for example, not rectify mistakes occurring during the production process without precise instructions from their superiors, this does not harm the pursuit of PI strategies, as product quality is less important than product costs.[21]

This reasoning makes it possible to derive three testable hypotheses on the importance of different types of employee skill for diverse competitive strategies:

H1. General employee skills facilitate RPI strategies, whereas

H2. Specific skills of employees are conducive to IPI strategies.

H3. PI strategies require employees with neither specific nor general but low skills.

To assess the relative importance of skill types for RPI, IPI, and PI strategies, their explanatory power needs to be tested against the impact of rival explanations. The analytical reason is straight-forward: while a correlation between two variables can be statistically significant in absolute terms, it can become relatively insignificant as soon as other, more strongly correlating factors are introduced into the analyses. Various contributions to the strategy literature highlight that a firm's age is a particularly good predictor of its competitive strategy,[22] because radical innovations are usually introduced by the newcomers to an industry. Incumbent firms typically propose incremental rather than radical innovations, because their own products risk becoming obsolete whenever radically new goods assert themselves on the market (Utterback, 1994: 90–101, 160–165, 223–236). Hence, young corporate age seems to be conducive to the pursuit of RPI strategies because young firms have hardly any products that could become obsolete if radical innovations are introduced. The opposite line of reasoning applies to the incumbents of an industry. To test the relative impact of skill types on RPI, IPI, and PI strategies against the influence of corporate age, the following rival hypothesis is formulated:

H4. (a) Young corporate age facilitates RPI strategies, whereas (b) advanced corporate age is conducive to IPI and (c) PI strategies alike.

Note that other factors than corporate age and employee skills are identified in the literature that can influence whether firms pursue RPI, IPI, or PI strategies. These factors include, most importantly, the *size of a company* (measured by the number of employees): Small firms typically find it easier to be radically innovative because they can move out of established, and into entirely new, product segments faster than large firms (Utterback, 1994). Furthermore, the broader institutional environment of a *country* is said to influence the competitive strategies pursued by firms: Extending their arguments to institutions beyond labour markets, the VoC and NIS scholars argue that the institutional environment of liberal economies, such as the UK, facilitate RPI strategies, while institutions of coordinated economies like Germany motivate firms to pursue IPI strategies, whereas the low cost competitiveness facilitated by Italy's institutions is said to facilitate PI strategies (Lundvall, 1992a; Nelson, 1993; Hall and Soskice, 2001b).

For the sake of parsimony, and to spare the reader tests of hypotheses that do not deliver meaningful insights, it should be noted that neither of these two theories demonstrated to have statistically significant explanatory power. While a firm's *country* turned out not to have any significant impact on competitive strategies ($r = -0.20$; $p > 0.5$), a *firm's size* regressed on its own significantly influences whether, or not, firms pursue RPI strategies ($r = -0.273$; $p < 0.05$). But since young firms typically have notably less employees than mature companies, the two predictors *corporate size* and *corporate age* are highly correlated ($r = 0.454$; $p < 0.001$). Consequently, they cannibalize on each others' explanatory power to the extent that both indicators become statistically insignificant as soon as they are regressed jointly on competitive strategies. In order to allow for the explanatory power of corporate age, the strongest alternative determinant of competitive strategies, to emerge most clearly against the influence of employees skills, corporate size is not included in the following analyses.

To conceptualize the notions of *general* and *specific skills*, the VoC scholars draw on the work of Becker (1975 in Estevez-Abe et al., 2001: 148), who defines *specific skills* as those qualifications that employees can use only within one single firm (Becker, 1975: 26–27). Accordingly, workers gain specific skills through long-term employment at one company, or through participation in specific training courses that 'increase the future marginal productivity of workers [only] in the firm providing it' (Becker, 1975: 19). On the other hand, *general skills* are conceptualized as those qualifications that employees can use in all firms requiring certain business functions (Becker, 1975: 19–20). Consequently, workers gain general skills by changing jobs frequently, or by participating in courses that provide 'general training [which] increases the marginal productivity of trainees by exactly the same amount in the firms providing the training as in other firms' (Becker, 1975: 26).

While Becker's conceptualizations are theoretically highly consistent, they are hardly observable in real life as employees typically hold a mixture of general and specific skills. In addition, the VoC contributors (Estevez-Abe et al., 2001: 148) highlight that *industry-specific skills* constitute a third skill category along with general and specific qualifications. In line with Becker's reasoning, industry-specific skills are defined as those qualifications that employees can use in all firms within the same industry as they gain them via apprenticeships and vocational training. Consequently, industry-specific skills increase the marginal productivity of all employees that have undergone such training courses within one industry. To remain in line with the conceptualizations of the VoC literature, *specific skills* are here defined as narrowly employable qualifications – usually a combination of industry- and firm-specific skills – which employees can use only within one industry as they are taught through apprenticeships or similar vocational training programmes. *General skills*, on the other hand, are defined as widely employable qualifications that employees can use across industries because they are transmitted through educational programmes other than apprenticeship and vocational training.

How to operationalize these concepts? Structured interviews with Human Resource (HR) officers turned out to be the only source available to learn about the skill types which are employed by those 102 firms that we identified as RPI, IPI, and PI strategists in Section 2. Overall, HR managers of 69 firms agreed to give an interview. All interviews were conducted by one of the authors in the native language of the interviewee (German, English, or

[21] See footnote 6.

[22] See Levitt (1965), Klepper and Graddy (1990), Utterback (1994), Klepper and Simons (1997), and Walker (2003): chapter 4.

Table 2
Skill profiles of entire workforce employed by RPI, IPI, and PI strategists.[a]

Group of firms	No. of cases	Skill specificity (the higher the score, the more specific the skills)	Skill generality (the higher the score, the more general the skills)	Total (maximum score obtainable)
RPIs UK	7	1.4	3.6	5
IPIs UK	8	3.4	1.6	5
PIs UK	4	2.0	3.0	5
RPIs Germany	7	1.7	3.3	5
IPIs Germany	12	3.7	1.3	5
PIs Germany	9	3.1	1.9	5
RPIs Italy	7	1.7	3.3	5
IPIs Italy	10	3.7	1.3	5
PIs Italy	4	2.3	2.7	5
RPIs overall	*21*	*1.6*	*3.4*	*5*
IPIs overall	*30*	*3.6*	*1.4*	*5*
PIs overall	*17*	*2.6*	*2.4*	*5*
Total	68	2.7	2.3	5

Source: own calculations based on 68 interviews with HR managers in British, German, and Italian pharmaceutical firms.
[a] The specificity and generality index rank skill profiles of employees on a scale from 0 to 5.

Italian) between March 2004 and March 2006. The information obtained from these interviews serve as the empirical basis for all following analyses. To begin with, a micro-level indicator of skill profiles was composed. This indicator takes all those aspects into consideration which the VoC contributors retain as essential for employees to acquire specific skills: *employment tenure*,[23] *vocational training*,[24] and *on-the-job training*.[25] For each firm studied, points were assigned according to these aspects and added up to one 'skill specificity' index, as well as one 'skill generality' indicator. Given that the two indices assume reversed scores, the following passage only explains how the skill specificity index was computed.

A maximum of 5 points was attributed to a firm according to the specificity of its employees' skills. Out of this, up to 2 points were awarded for the *average job tenure* of a firm's employees. Whenever the latter was below 4 years, no points were attributed because employees were assumed not to work long enough in the same job to acquire specific skills. One point was awarded for average tenure between 4 and 7.9 years, while two points were granted whenever job tenure was higher than 8 years because employees were assumed to gain thorough insights into how their firm operates.[26] Furthermore, it was taken into consideration whether firms *employ former trainees*. Whenever firms did not offer (vocational) training programmes, or did offer programmes without aiming at employing trainees at the end, they were awarded no specificity points, because companies were assumed to perceive trainees as a source of cheap labour rather than as an opportunity to equip future employees with specific skills. Accordingly, one point was assigned to those firms that employed trainees upon completion of their (vocational) training programme. Finally, the *annual on-the-job training* offered by the interviewed firms was considered as a third criterion to measure their employees' skill specificity. No points were granted to a firm that either offered on-the-job training to less than 50% of their workforce, or that offered training courses which advised employees mostly in general skills. One point was assigned whenever a firm offered on-the-job training to at least 50% of its workforce, whereby mostly industry-specific skills were taught. Two points were attributed whenever a firm provided annual on-the-job training to at least 50% of its employees, transmitting primarily firm-specific skills.[27]

An overview of the skill specificity and, respectively, generality of employees working for RPI, IPI, and PI firms is provided in Table 2. It is interesting to note that firms competing through the same strategy seem to employ workforces with similar skill profiles, irrespective of whether they are located in Italy, Germany, or the UK. This indicates that variations in skill profiles are influenced by the strategy pursued rather than by the E&T system of the country in which a company is active. What is more, Table 2 also provides empirical evidence in support of hypotheses H1–H3 as RPI pursuers predominantly employ workforces with general skills, whereas IPI strategists rely on employees with specific skills. PI firms, in turn, seem to hire employees that hold neither distinct specific nor general skills.

But are these differences in employee skills statistically significant? Three sets of multinomial logistic regression analyses shed light on this question. To improve the readability of the outcome, the original skill specificity scale ranging from 0 to 5 points was transformed into a scale ranging from 0 to 100 points.[28] Given that the specificity and the generality indices assume reversed scores, the same results are obtained for both indices with the exception of the directional measures which take on opposite values. To avoid repetitions, all three regression sets therefore use only the specificity index. More concretely, models 1 and 2 assess the individual explanatory power of *skill specificity* and *corporate age* (as the model's respective independent variable) by regressing both factors separately on *competitive strategy* (dependent variable).[29] In model 3, the relative importance of *skill specificity* and *age* (independent variables) is assessed by regressing both factors jointly on *competitive strategy* (dependent variable). The multinomial logistic regression analysis of model 3 can thus be written as the following

[23] See Estevez-Abe et al. (2001): 145, 150–151, Hall and Soskice (2001a): 27, 41, Casper and Whitley (2004): 94–95.
[24] See Hall and Soskice (2001a): 25, 30 and Casper and Whitley (2004): 94–95.
[25] See Becker (1975); see also Lindbeck and Snower (2001).
[26] The reason for having chosen 4 and 8 years as thresholds is that the first and second promotions usually take place within these time spans, and an employee's decision to switch companies tends to be significantly influenced by a firm's attitude towards promotion. Yet, interviews also revealed that employees are less likely to leave a firm, the longer they work for it. For this reason, further thresholds (e.g. 12 years) were not introduced.

[27] The complete questionnaire used to enquire about the skill profiles of a firm's workforce are made available by the author upon request.
[28] This was done by multiplying all original values by a factor of 20.
[29] Distinguishing between three discrete categories, the strategy variable assigns a value of '1' to any firm that pursues an RPI strategy, a value of '2' to any IPI pursuer, and a value of '3' to any PI strategist.

equation:

$$\text{Odds}_{\text{RPI/PI}} = \frac{\text{prob}_{\text{RPI}}}{\text{prob}_{\text{PI}}} = e^{\beta_{10}+\beta_{11}\ \text{skill specificity}+\beta_{12}\ \text{corportate age}} \quad (1)$$

$$\text{Odds}_{\text{IPI/PI}} = \frac{\text{prob}_{\text{IPI}}}{\text{prob}_{\text{PI}}} = e^{\beta_{20}+\beta_{21}\ \text{skill specificity}+\beta_{22}\ \text{corportate age}} \quad (2)$$

The results obtained from these analyses are reported in Table 3. It should be noted that these outcomes were obtained from analyzing the entire dataset of 69 pharmaceutical firms. To reveal possible country-specific variations, the respective regressions were however re-run for each country separately. Even though the number of cases per country was sometimes too limited to produce statistically significant figures, the country-specific analyses generally confirmed the results reported in Table 3. Irrespective of the country under investigation, the same skill type turned out to have a particularly strong influence on one rather than on the two other competitive strategies. These findings underline the idea that firms need employees with distinct skill profiles to pursue RPI, IPI, and PI strategies because they do not randomly hire workforces with those skill profiles that are abundantly provided by their country's E&T system. Given that the country-specific analyses revealed no noteworthy national variations, the results obtained from the overall sample are presented in Table 3 and discussed in the following.

The regression analyses conducted confirm the trends reported in Table 2. In line with hypotheses H1–H3 pharmaceutical firms hire employees with distinct skill profiles to pursue RPI, IPI, and PI strategies. Accordingly, models 1 and 3 show that *radical product innovators* substantially employ people with general skills. More precisely, model 3 reveals that – when controlled for corporate age – a 1% decrease in the specificity or, respectively, a 1% increase in the generality of skills held by a firm's workforce raises the likelihood that this firm pursues an RPI rather than an IPI strategy by 12.1%. At the same time, it raises the probability that the firm pursues an RPI rather than a PI strategy by 4.8% (1 − 0.952 = 0.048). These findings confirm hypothesis H1 in that employees with general skills foster radical product innovation. In the same vein, models 1 and 3 reveal that *incremental product innovators* importantly rely on workforces with specific skills. Accordingly, model 3 demonstrates that, even when controlled for corporate age, a 1% increase in the skill specificity of a firm's employees leads to an increase in the odds of this firm being an IPI rather than an RPI strategist by 12.1%, while the odds of the firm being an IPI rather than an PI strategist increase by 6.3% (1 − 0.937 = 0.063). These insights lend analytical support to hypothesis H2: workforces with specific skills positively influence incremental product innovation. Finally, it is remarkable that the skill types employed by *product imitators* are significantly different from those of RPI and IPI firms. Accordingly, model 3 shows that a 1% decrease in the generality or, respectively, a 1% increase in the specificity of the skills held by a workforce increases the probability that the employing firm pursues an PI rather than an RPI strategy by 4.8% (1 − 0.952 = 0.048). Similarly, a 1% decrease in the specificity or, respectively, a 1% increase in the generality of the skills held by a workforce increases the likelihood that the employer is a PI rather than an IPI strategist by 6.3% (1 − 0.937 = 0.063). Combined with the insights gained from Table 2, these results confirm hypothesis H3: PI strategists mostly employ people with undifferentiated skill profiles because this, presumably less expensive, combination of specific and general skills facilitates product imitation.

It is furthermore noteworthy that the explanatory power of *corporate age* – the strongest rival predictor of RPI, IPI and PI strategies – turns out to be both strong and statistically significant in model 2. At first sight, this confirms hypothesis H4 as young corporate age is positively correlated with RPI strategies (hypothesis H4a), while mature corporate age positively correlates with IPI and PI strategies (hypothesis H4b and c). For each additional year a firm exists, the odds of it pursuing an IPI rather than an RPI strategy increase by 3.3%, whereas the odds of a firm pursuing an PI rather than an RPI strategy increase by 2.8% (1 − 0.972 = 0.028). Importantly, however, the impact of different skill profiles on RPI, IPI, and PI strategies is so pronounced that corporate age becomes statistically insignificant as soon as both variables are regressed jointly in model 3. This allows us to deduce that employees with distinct skill profiles are an important precondition for the pursuit of RPI, IPI, and PI strategies – seemingly more important than the firm's age.

To conclude, the micro-level analyses of Section 3 have provided empirical support for the VoC arguments. While firms require employees with general skills to pursue RPI strategies, they rely on workforces with specific skills for IPI strategies. PI strategies, in turn, seem to benefit from workers that hold neither general nor specific skills. Such a discretionary skill mixture seems less costly than distinct skill generality or specificity because the employing firm needs neither to invest in specific education and training, nor to incur high search costs because employees change jobs less frequently.

4. The NIS reasoning: how scientists with different knowledge backgrounds facilitate RPI, IPI, and PI strategies

Will equivalent analyses lend support to the NIS arguments on the knowledge base of scientists? Having a slightly different focus than the VoC contributors, the NIS literature starts from the observation that systematic differences exist in the organization of national research systems. In *flexible research systems*, senior scientists are neither civil servants, nor do they enjoy unilateral decision-making power regarding the projects they wish to pursue and the collaborators they want to employ. Instead, only the most promising and rewarding research projects are funded and the best performing scientists recruited. Since these scientists often come from different universities, countries, and disciplines, research teams tend to include scientists with *heterogeneous knowledge*.[30] Heterogeneous scientific knowledge, in turn, seems to facilitate RPI strategies as the latter require 'an enormous intellectual effort or an extremely creative mind to identify a potential new combination.' (Lundvall, 1992b: 8; see also Johnson, 1992: 29). Scientists who have worked in diverse environments collaborating with researchers from different universities, countries, and disciplines are more likely to have this innovative potential due to their high imaginative capacities. To be radically innovative, firms are thus said to rely on scientists with heterogeneous knowledge.

The opposite holds true for *rigid research systems*, where scientists tend to follow a career in close collaboration with one university or research institute. While tenure positions are limited and hard to obtain, those scientists who get tenured become civil servants and enjoy noteworthy autonomy in choosing their research projects and collaborators. Given that the careers of junior scientists heavily depend on the support of these senior scientists, the former entertain long-lasting employment relationships with their *Doktorvater*.[31] This implies that the knowledge of scientists working in one research area is *homogenous* in that senior scientists rarely change their research focus, while junior scientists collaborate closely and for a long-time with them. Homogeneous

[30] See Hollingsworth (2000): 626–630, Hollingsworth and Hollingsworth, 2000; see also Walker (1993), Patel and Pavitt (1994), Freeman and Soete (1997b).

[31] See Hollingsworth (2000): 626–630; see also Dalum et al. (1992): 302–303, Keck (1993), Patel and Pavitt (1994), Freeman and Soete (1997b).

Table 3
Importance of skill specificity and corporate age for RPI, IPI, and PI strategies. (Results of multinomial logistic regression analyses: exponential B).

Model	1			2			3		
Comparing	IPI	PI	RPI	IPI	PI	RPI	IPI	PI	RPI
to reference category	RPI	IPI	PI	RPI	IPI	PI	RPI	IPI	PI
Independent variables									
Skill specificity	1.126***	0.940***	0.945***	–	–	–	1.121***	.937***	.952**
Corporate age	–	–	–	1.033***	.996	.972**	1.008	1.003	.989
N	68			69			68		
$R^2_{\text{Nagelkerke}}$	0.529			0.204			0.539		

Significance levels: *<0.10; **<0.05; ***<0.01. Constant not reported in table.

scientific knowledge, in turn, is said to promote IPI strategies as scientists are used to work within the same field, collaborating with the same team, for a long time. Accordingly, they not only have an in-depth understanding of the technological opportunities in this area, they are also used to cooperating and to combining their insights, thereby developing incremental innovations. At the same time, scientists with homogeneous skills can be so familiar with one environment that they may find it difficult to imagine entirely new scenarios. They tend to lack the creative capacity for being radically innovative.

Finally, firms that pursue imitation strategies do, by definition, not engage in research and development activities and, hence, save costs by not employing scientists.[32]

This reasoning makes it possible to derive three testable hypotheses on the importance of different types of scientific knowledge for RPI, IPI, and PI strategies:

H5. Scientists with heterogeneous knowledge facilitate the pursuit of RPI strategies, whereas

H6. Scientists with homogeneous knowledge are at the basis of IPI.

H7. PI strategies benefit from no scientific knowledge.

In line with Section 3, the relative importance of diverse scientific knowledge is tested against the impact of a firm's age, i.e. the most important rival explanation for how firms can pursue RPI, IPI, and PI strategies. Hence, hypothesis 4 remains the same:

H4. (a) Young corporate age is conducive to the pursuit of RPI strategies, whereas (b) advanced corporate age promotes both IPI and (c) PI strategies.

Given that most NIS scholars do not test their claims at the micro level (for two exceptions, see Hollingsworth and Hollingsworth, 2000; Nooteboom et al., 2007), but rather illustrate how the innovative performance of countries differs as a function of their research systems, clear-cut conceptualizations of *heterogeneous* and, respectively, *homogeneous scientific knowledge* are not provided by the literature. It is however clear from the NIS reasoning that the *variety* of information exchanged by scientists is key to the novelty of the type of innovations they make.[33] The present study therefore follows the NIS literature by taking the variety of universities, disciplines, and countries from which scientists originate as an indicator of their knowledge diversity.

To measure this knowledge diversity, a new indicator was composed on the basis of the interviews conducted with 69 HR managers of those RPI, IPI and PI firms whose competitive strategies were identified in Section 2. Hence, HR managers were asked to report not only about the skill types of their firm's entire workforce, as illustrated in Section 3, but also about the knowledge diversity of the firm's scientists. More precisely, HR managers were asked to indicate from how many different disciplines, countries and universities their researchers originate.

This information was used to calculate a 'knowledge homogeneity index' which reports the average frequency with which a firm's scientists have a similar knowledge background. For more clarity, consider the following example. Imagine a company employing 60 researchers who originate from 15 universities, 6 countries, and 3 disciplines. This means that every 4th (=60/15) scientist comes from a different university, every 10th (=60/6) scientist originates from a different country, and every 20th (=60/3) scientist comes from a different discipline. Thus, on average, every 11th (=(4 + 10 + 20)/3) researcher has a dissimilar knowledge background. This measurement implies that higher scores indicate higher skill homogeneity. In other words, the higher the index scores, the more homogeneous and the less heterogeneous the knowledge backgrounds of a firm's scientists.

To make the heterogeneity of scientific knowledge explicit, a 'knowledge heterogeneity index' was derived from the knowledge homogeneity index. Assuming that the highest score of knowledge homogeneity observed, namely 119, also constitutes the highest value which this index can at all take on, 119 was taken as the upper benchmark. Consequently, the knowledge heterogeneity index was calculated for each firm by assigning it the reversed score of the knowledge homogeneity index:

$$\text{Scientific knowledge heterogeneity} = 119 - \text{scientific knowledge homogeneity}$$

Higher scores on the heterogeneity index thus indicate that the scientists employed have more heterogeneous knowledge in that every n-th scientist has a similar knowledge background.

Table 4 provides an overview over the results obtained. Akin to the skill types of the firms' entire workforce (see Section 3), *country-specific* variations in the knowledge background of scientists employed by RPI, IPI, and PI strategists are minor. Irrespective of the country in which firms operate, the scientists working for RPI firms have similarly heterogeneous backgrounds, whereas their colleagues working for PI firms have about the same homogeneous knowledge bases. Interestingly, the interviews carried out revealed that PI strategists do, without exception, not employ scientists with the aim of discovering or developing radical or incremental innovations. Instead, scientists focus on imitating the innovations made by competitors – if this task of drug imitation has not been outsourced after all. The scientists employed at PI firms thus have clear instructions regarding the purpose of their work, and the means and methods to be employed, so that their tasks are production- rather than R&D-oriented.

Consequently, Table 4 does not only suggest that RPI, IPI, and PI strategists cannot randomly hire scientists but rather need distinct knowledge backgrounds to pursue these strategies; it also indicates support for hypotheses H5–H7. Scientists with heterogeneous knowledge seem to facilitate RPI strategies (H5), whereas scientists

[32] See also footnote 7.

[33] See Freeman and Soete (1997a), Hage and Hollingsworth (2000), Hollingsworth (2000): 626–630, Hollingsworth and Hollingsworth (2000), Nooteboom et al. (2007).

Table 4
Knowledge homogeneity of scientists employed by RPI, IPI, and PI strategists.

Group of firms	No. of cases	Knowledge homogeneity of scientists[a]	Knowledge heterogeneity of scientists[b]
RPIs UK	5	3rd	116th
IPIs UK	8	25th	94th
PIs UK	4	0	0
RPIs Germany	6	6th	113th
IPIs Germany	10	53rd	66th
PIs Germany	9	0	0
RPIs Italy	7	10th	109th
IPIs Italy	10	37th	82nd
PIs Italy	4	0	0
RPIs overall	18	7th	112th
IPIs overall	28	39th	80th
PIs overall	17	0	0
Total/average (excluding PIs)	63	27th	92nd

Source: own calculations based on 63 interviews with HR managers in British, German, and Italian pharmaceutical firms.
[a] The knowledge homogeneity index illustrates with which average frequency scientists come from different universities, disciplines, and countries. Consequently, the higher the scores, the more homogeneous is the scientific knowledge of the employing firm in that every *n*-th respectively scientist has a *different* knowledge background.
[b] The knowledge heterogeneity index assumes the reversed scores of the knowledge homogeneity index. Consequently, the higher the scores, the more heterogeneous is the scientific knowledge of the employing firm in that every *n*-th scientist has a *similar* knowledge background.

with homogeneous knowledge are at the basis for IPI (H6), while PI strategies benefit from no scientific knowledge (H7).

Quantitative analyses reveal the statistical robustness of these observations. Given that PI strategists do not employ scientists engaged in R&D activities, they need to be excluded from these analyses, because a perfect split between PI and non-PI firms on the scientific knowledge variable deprives the dataset of the necessary variation. Consequently, three binary logistic regression analyses are carried out to assess the importance of different knowledge backgrounds of scientists for RPI and IPI strategies. To facilitate the readability and comparability of the outcome, the original scientific knowledge scale ranging from 0 to 117 points was transformed into a scale ranging from 0 to 100 points.[34] While the first analysis (model 1) tests the impact of *scientific knowledge heterogeneity*, the second analysis (model 2) assesses the impact of *corporate age* (as the respective independent variable) on RPI (dependent variable).[35] The third analysis (model 3) finally reveals the relative importance of *scientific knowledge heterogeneity* by regressing it together with *age* (independent variables) on RPI (dependent variable). Consequently, model 3 can be written as the following equation:

$$\text{Odds}_{\text{RPI/IPI}}=\frac{\text{prob}_{\text{RPI}}}{\text{prob}_{\text{IPI}}}=e^{\beta_0+\beta_1\,\text{skill knowledge heterogeneity}+\beta_2\,\text{corportate age}}$$

In line with Section 3, these analyses were also replicated at the country level. Given that none of them revealed noteworthy country-specific differences, it can be concluded that RPI and IPI firms cannot randomly hire scientists with those knowledge backgrounds which are fostered by national research systems. Instead, RPI and IPI firms need to employ particular types of scientific knowledge. Table 5 reports the results obtained on the basis of the overall sample.[36] These results indicate support for the hypotheses that heterogeneous scientific knowledge is required for the pursuit of RPI strategies, whereas homogeneous scientific knowledge is necessary for IPI.

More concretely, the results of Table 5 corroborate hypotheses H4 that young corporate age is conducive to the pursuit of RPI strategies (H4a), whereas mature corporate age promotes IPI (H4b). Accordingly, model 2 reveals that, everything else being equal, the odds of firms pursuing an RPI rather than an IPI strategy increase by 2.7% (1 − 0.973 = 0.027) for each additional year of corporate age. Interestingly, though, model 3 indicates that a firm's age is statistically insignificant compared to the knowledge held by scientists. This allows us to conclude that scientific knowledge constitutes a crucial impact factor for RPI and IPI strategists, which has an even more substantial impact on competitive strategies than a firm's age.

Furthermore Table 5 confirms the observations made on the basis of Table 4. In line with hypotheses H5, model 1 shows that RPI strategists employ significantly more scientists with a heterogeneous background than IPI pursuers. This is confirmed by model 3 which indicates that, when controlled for corporate age, every increase by one percent in heterogeneous scientific knowledge leads to an increase in the odds of the firm pursuing an RPI rather than an IPI strategy by 45.5%. This supports the claims of hypotheses H5 and H6: that scientists with heterogeneous knowledge facilitate RPI (H5), whereas scientists with homogeneous knowledge support IPI (H6). Albeit not investigated by the above regression analyses, also hypothesis H7 is empirically supported to the extent that HR interviewees repeatedly pointed out that the employment of scientists pursuing R&D projects is unnecessary for PI strategies. We can thus consider H7 as confirmed: PI firms benefit from no scientific knowledge.

5. Contrasting the VoC and NIS reasoning: employee skills versus scientific knowledge

The previous parts have shed light on the first research question posed in the beginning of this article: whether micro-level data confirm the VoC and NIS arguments on the importance of different qualification types for RPI, IPI, and PI strategies. Interviews with HR mangers have supported the arguments of both the VoC literature claiming that *employees* with particular skill types are required for each strategy (Section 3), and of the NIS reasoning sustaining that *scientists* with particular knowledge backgrounds facilitate RPI, IPI, and PI strategies (Section 4).

[34] This was done by multiplying all values with the fraction of 100/117.
[35] Distinguishing between two discrete categories, the strategy variable assigns a value of '1' to any firm that pursues an RPI strategy and a value of '0' to any IPI pursuer.
[36] Given that the knowledge heterogeneity index assumes the reciprocal values of the knowledge homogeneity index, the results obtained from binary logistic analyses which regress homogeneous scientific knowledge and corporate age on IPI strategies are identical to the results reported in Table 5.

Table 5
Importance of scientific knowledge heterogeneity and corporate age for RPI (results of binary logistic regression analyses: exponential B).

Independent variables	Model 1	Model 2	Model 3
Heterogeneous scientific knowledge	1.433***	–	1.455***
Corporate age	–	0.973**	1.007
N	46	46	46
R^2 Nagelkerke	0.722	0.263	0.725

Significance levels: *<0.10; **<0.05; ***<0.01. Constant not reported in table.

However, it is still unclear whether the VoC and the NIS literatures ultimately propose the same arguments, merely focusing on different groups of employees. Given that scientists hold the key knowledge required for innovation, it could be sufficient if scientists alone have the respective knowledge backgrounds for enabling the pursuit of RPI, IPI, and PI strategies. Consequently, the VoC literature might overlook that variations in the skill mixture of the firms' entire workforces ultimately stem from the knowledge diversity of scientists. Alternatively, it could be possible that all employees, of which scientists are just one part, require particular skill types in order to allow RPI, IPI, and PI firms to pursue their strategies. Consequently, the NIS literature might overlook that variations in the knowledge diversity of scientists are simply representative of the skill diversity of all employees. Finally, it could be possible that RPI, IPI, and PI strategists need employees, including scientists, who have undergone particular education and training in order to develop the necessary skill profiles. In addition, it could be necessary that a firm's scientists must have worked in, and been recruited from, homogenous or heterogeneous backgrounds respectively. In this case, the VoC and NIS literatures would describe different phenomena and, despite their similar reasoning, propose different arguments.

Thus, the following hypotheses can be formulated:

H8. To pursue RPI, IPI, and PI strategies, firms only need employees with distinct skill profiles, whereas scientists with particular knowledge backgrounds are not required.

H9. To pursue RPI, IPI, and PI strategies, firms do not need employees with distinct skill profiles, but only require scientists with particular knowledge backgrounds.

H10. To pursue RPI, IPI, and PI strategies, firms need employees with distinct skill profiles, as well as scientists with particular knowledge backgrounds.

In line with Sections 3 and 4, the relative importance of skill profiles and scientific knowledge is tested against the impact of corporate age, so that hypothesis H4 remains the same:

H4. (a) Young corporate age is conducive to the pursuit of RPI strategies, whereas (b) advanced corporate age promotes both IPI and (c) PI strategies.

To test these hypotheses, five sets of binary logistic regression analyses are carried out.[37] The first two sets (models 1a–c and 2a–c) partly repeat our previous analyses in that models 1a–c test the individual impact of *skill generality*, *knowledge heterogeneity*, and *corporate age* (independent variables) on *RPI strategies* (dependent variable), while models 2a–c assess the joint impact of any combination of these two variables. The importance of *skill generality* and *knowledge heterogeneity* together with their *interaction effect* on the one hand, and *corporate age* on the other, is tested in models 3a and b. Model 4 assesses the relative influence of all four predictors on *RPI strategies*. Akin to the skill generality and the knowledge heterogeneity indices, the scale of the interaction effect was standardized to a range of 0–100.[38]

Importantly, though, severe multicollinearity problems arise whenever skill generality and knowledge heterogeneity are regressed together with their interaction effect in models 3a and 4, because the interaction is strongly correlated with its components. Consequently, the average variance inflation factor (VIF) of model 3a equals 36.9 and is 28.9 for model 4. Since Bowerman and O'Connell (1990) argue that an average VIF > 1 can already lead to serious distortions of the regression coefficients, it is hardly surprising that neither the coefficients in model 3a nor in model 4 turn out to be statistically significant.

Given that this article is particularly interested in the joint effects of skill generality and knowledge heterogeneity, model 5 additionally explores the relative explanatory power of both variables and their interaction effect with the help of the 'stepwise forward' method. Contrary to the traditionally used 'enter' method which forces all independent variables jointly into one regression model, the 'stepwise forward' method identifies the strongest predictors one by one. It does so by defining an initial model that contains only the constant (β_0). The stepwise forward algorithm then searches for that predictor (out of all the independent variables inserted in the model) which best predicts the outcome variable. '[I]t does this by selecting the predictor that has the highest simple correlation with the outcome. If this predictor significantly improves the ability of the model to predict the outcome, then [it] is retained in the model and the [algorithm] searches for the second strongest predictor, [i.e.] the variable that has the largest semi-partial correlation with the outcome' (Field, 2009: 212–213). This procedure is repeated until all independent variables are either fitted into, or excluded from, the model because variables that do not significantly increase the predictive power are not retained in the final model.

Models 5a and b use this stepwise forward method to further explore the explanatory power of employee skills, scientific knowledge, their interaction effect, and corporate age. While model 5a regresses the *skill generality* and *knowledge heterogeneity* indices together with their *interaction effect* (independent variables) on *RPI strategies* (dependent variable), model 5b includes *corporate age* as a further predictor of RPI strategies. The results of these analyses are reported in Table 6. In line with the previous regression analyses, Table 6 reports the results obtained from the entire dataset, because replications of the various analyses at the country level did not reveal any noteworthy variations.

What do these results teach us? Overall, they provide empirical support for the VoC arguments, as well as the NIS reasoning: that both skill profiles of employees and knowledge background of scientists 'matter' for RPI strategies. More precisely, they matter as follows. In Sections 3 and 4, we already discovered that the

[37] In line with Section 4, multinomial logistic regressions cannot be used because the perfect split between PI and non-PI firms on the scientific knowledge variable and, hence, on the interaction effect between the skill and the knowledge indices deprives the data of the necessary variation. Consequently, PI firms cannot be included in the analyses.

[38] This was done by multiplying all values with the fraction of 100/858.

Table 6
Importance of skill generality and scientific knowledge heterogeneity for RPI (results of binary logistic regression analyses: exponential B).

Independent variables	Models 1a–c (individual impact of 1 predictor)			Models 2a–c (joint impact of 2 predictors)			Models 3a and b (joint impact of 3 predictors)		Model 4 (4 predictors)	Models 5a and 5b (joint impact of the 2, 3, and 4 most relevant predictors)	
Regression method	Forced entry 'Enter'									Stepwise entry: 'Forward'	
Skill generality	1.136***			1.114**	1.139***		*0.566*	1.251*	*0.610*	Not retained	Not retained
Heterogeneous scientific knowledge		1.433***		1.324**		1.455***	*0.966*	1.538**	*1.103*	Not retained	Not retained
Interaction effect: skill generality × scientific knowledge heterogeneity							*2.143*		*2.213*	1.154***	1.154***
Corporate age			.973**		1.002	1.007		1.080	*1.074*		Not retained
N	46	46	46	46	46	46	46	46	46	46	46
$R^2_{Nagelkerke}$	0.736	0.722	0.263	0.843	0.737	0.725	0.851	0.898	0.902	0.799	0.799

Significance levels: * <0.10; ** <0.05; *** <0.01. Constant not reported in table. Italic numbers indicate distorted coefficients due to multicollinearity problems: average $VIF_{Model\ 3a} = 36.9$; average $VIF_{Model\ 4} = 28.9$.

skill profiles of a firm's employees and, respectively, the knowledge backgrounds of its scientists are strong predictors of the firm's competitive strategy – not only on their own (see models 1a and 1b), but also when controlled for corporate age (as in models 2b and 2c). The most insightful results of Table 6 therefore concern the joint impact of employees' skill profiles and scientists' knowledge backgrounds. In this regard, models 2a and 3b are particularly revealing. Model 2a teaches us that, when controlled for each other, both indices are equally significant predictors of RPI strategies: The odds of firms pursuing RPI rather than IPI strategies increase by 11.4% for each percent increase in the skill generality of a firm's workforce, while they increase by 32.4% for each additional percent of heterogeneity in the scientists backgrounds. This finding is corroborated by model 3b: Both qualification indicators remain significant predictors of a firm's competitive strategy even when they are controlled for corporate age which, in turn, becomes statistically insignificant as a strategy predictor. These findings cast doubt on hypotheses H8 and H9 as they suggest, in line with hypothesis H10, that skill profiles and scientific knowledge measure two different rather than the same concepts.[39] In other words, a firm's chances to pursue RPI rather than IPI strategies increase by 10.7% ($R^2_{\text{Nagelkerke Model 2a}} - R^2_{\text{Nagelkerke Model 1a}} = 0.107$) if companies do not only have employees with general skills ($R^2_{\text{Nagelkerke Model 1a}} = 0.736$) but also scientists with heterogeneous knowledge ($R^2_{\text{Nagelkerke Model 2a}} = 0.843$). Similarly, the odds of a company pursuing RPI rather than IPI strategies increase by 12.1% ($R^2_{\text{Nagelkerke Model 2a}} - R^2_{\text{Nagelkerke Model 1b}} = 0.121$) if they employ not only scientists with heterogeneous backgrounds ($R^2_{\text{Nagelkerke Model 1b}} = 0.722$) but also a workforce with general skill profiles ($R^2_{\text{Nagelkerke Model 2a}} = 0.843$).

Having established that employee skills and scientific knowledge are of additive importance for corporate strategies, the question remains whether they also have an exponential effect. In other words, are firms hiring workforces with adequate skill profiles and scientists with appropriate knowledge 'only' proportionately or 'even' exponentially better in pursuing the chosen competitive strategies? As mentioned previously, models 3a and 4 cannot answer this question because all regression coefficients become statistically insignificant due to the high multicollinearity of the interaction effect. Interestingly, though, models 5 reveal that the interaction effect is the strongest, and only, predictor of RPI strategies. When the two qualification variables are regressed together with their interaction (model 5a) on the basis of the stepwise forward method, neither the skill generality nor the knowledge diversity indices are retained as further predictors of RPI in model 5a. These results are robust to the extent that not only the two qualification indices, but also corporate age, are excluded as predictors from model 5b. Hence, both models come to the same conclusion: For each unit increase of employees with general skills *in combination with* scientists with heterogeneous knowledge, the odds of a firm being an RPI rather than an IPI strategist increase by 15.4%.

It seems however unwise to assert a multiplicative interaction effect purely on the basis of a less conventional regression method. Furthermore, we should not forget that the number of observations is limited ($N = 46$). Let us therefore turn to qualitative insights gained from interviews with HR managers that shed light on how synergy effects arise whenever scientists with adequate knowledge backgrounds interact with employees holding appropriate skill profiles. HR managers of RPI strategists indicated that the innovative capacities of their firm's scientists was notably furthered by

[39] This conclusion is further supported by a reliability test which shows that Alpha Cronbach (0.088) is close to 0.

their exposure to many different ideas. RPI strategists therefore actively tried to facilitate such exposure: Remarkably, researchers were not only encouraged to visit external conferences and workshops. Also internal feedback mechanisms were systematically put in place – including, for example, regular meetings, internal workshops, or brown-bag lunch seminars with non-scientific employees from different departments. This exposure to different ideas was often perceived as vital for strengthening the radical innovativeness of scientists (Jon, 2004; Nokich, 2004; Manci, 2005; Sigillia, 2005). In a similar vein, HR managers of firms pursuing IPI strategies highlighted that not only their scientists but all employees working in key positions needed to be highly specialized in order to spot opportunities for product improvement. Furthermore, the interviewees stressed that improvement had many sources and did not necessarily come from scientists alone. Often propositions for change that translated into better products were made by manufacturing workers, who had pointed to possible modifications in the production process, or even by marketing and sales people, providing customer feedback. While some suggestions for improvement are implemented without involving scientific personnel, others serve as stimuli for researchers to develop better and, thus, incrementally innovative products (Jon, 2005; Maggi, 2005; Weel, 2005). In sum, the interaction between a firm's scientists and its non-scientific employees seems to be a vital source of ideas for incremental or, respectively, radical product innovations.

These findings disconfirm the hypotheses that either employees with distinct skill profiles (H8) or scientists with particular knowledge backgrounds (H9) are sufficient for pursuing RPI or IPI strategies respectively. Instead, they support hypothesis H10 as the pursuit of different strategies seems to be facilitated by a combination of employees and scientists with adequate qualifications. It is furthermore noteworthy how qualitative insights make it possible to *qualify* hypothesis H10 to the extent that the combination of employee skills and scientific knowledge seems to facilitate different strategies not in an *additive* but in a *multiplicative* manner. In other words, if both employees and scientists have those qualification types that facilitate the pursued strategy, their interaction creates synergies which enable a firm to be disproportionally better in pursuing their strategy than it would be if it had hired employee skills in isolation of scientific knowledge. This, in turn, suggests that employees and scientists alike have important innovative potentials which firms can use as sources for generating new ideas. Interestingly, though, this innovative potential is multiplied whenever employees and scientists do not act in isolation but collaborate and, possibly, learn from each other.

With regard to the VoC and NIS literatures, we can thus conclude that, despite their similar reasoning, they describe different phenomena, namely how diverse E&T and research systems endow people with diverse capacities to be either incrementally or radically innovative. At the same time, however, the VoC and NIS literatures can be criticized for not having taken the arguments of the neighbouring discipline into account. Had they done so, they would have realized that the combination of opportune employee skills and scientific knowledge enables firms to be disproportionately better in generating incremental or radical ideas than RPI and IPI strategists are when they merely hire the respective qualification types in isolation.

6. Conclusions: Two different literatures, one similar argument?

This article has studied the compatibility of the VoC and NIS arguments about the labour qualifications that firms need to hire in order to pursue strategies of radical product innovation (RPI), incremental product innovation (IPI), and product imitation (PI) respectively. Given that both literature strands base their arguments on similar lines of reasoning, while studying different groups of employees, it is unclear whether firms need to hire only scientists with particular knowledge backgrounds, only employees with distinct skill profiles, or both scientists and employees with the respective qualifications. It is furthermore striking that both literatures base their arguments on macro-level analyses and, with some very few exceptions,[40] have not tested their hypotheses on the basis of micro-level indicators.[41] The aims of this article were thus twofold: first, to assess whether micro-level data collected at the firm level supports the arguments of the VoC and NIS literatures; and, second, to understand whether RPI, IPI, and PI firms need scientists alone, an entire workforce, or both scientists and a workforce with distinct qualifications.

The results obtained from interviews with Human Resources managers in the UK, Germany, and Italy were straight-forward. Irrespective of the country in which firms are based, the latter require employees who have general skills for pursuing RPI strategies, employees with specific skills for IPI, and employees who do not hold particular skill profiles for PI strategies. Furthermore, RPI strategies are facilitated by scientists with a heterogeneous knowledge background, whereas IPI strategies benefit from scientists with homogeneous knowledge, while PI firms are best off if they do not at all hire scientists pursuing R&D activities. Micro-level data thus confirms the arguments of the VoC scholars on the one hand and the NIS literature on the other.

But what about the joint applicability of these theories? Do VoC scholars ignore that scientists with adequate knowledge backgrounds are sufficient for pursuing RPI and IPI strategies; are they mislead in their reasoning because variations in the workforces' qualifications ultimately result from variations in the firms' scientific knowledge employed? Or, do NIS scholars ignore that all employees of a firm need to have undergone particular education and training in order to acquire the necessary skills, so that the knowledge backgrounds of scientists merely represent the skill profiles of the entire workforce? Or, are the VoC and NIS arguments compatible in that firms need both employees with distinct skill profiles in addition to scientists with particular knowledge backgrounds? Again, the interviews with HR managers provided insightful answers. RPI, IPI, and PI strategists benefit from a combination of scientific knowledge and skill profiles: RPI strategies are facilitated by employees with general qualifications and scientists with heterogeneous knowledge backgrounds, whereas IPI rests upon a workforce with specific skills and scientists with homogeneous knowledge. PI firms, in turn, are best off if they neither hire scientists nor invest in educating and training their workforces. Interestingly, the combination of these qualification types seems to have a multiplicative rather than an additive impact. This means that firms which combine the respective employee and scientific qualifications are exponentially better in being radically or incrementally innovative than they would be if they hired these qualification types in isolation.

These findings have several noteworthy implications. First, they illustrate that the innovative potential of people is not concentrated in the scientists employed by a firm. New ideas can be generated by all employees, at all stages of the value chain. To stay innovative, firms would thus be misled to listen exclusively to the ideas proposed by their scientists. Second, and as a corollary of the first implication, scientists play a key role of innovation. This seems, however, less the case because scientists are active in R&D and, hence, in the knowledge-generating stages of the value chain. It rather results from the finding that scientists can

[40] See footnote 8.
[41] See footnote 9.

be holders of two different types of qualifications. Depending on their previous work experience and the composition of the team within which they work, scientists can have homogeneous or heterogeneous knowledge backgrounds. However, being part of the firm's entire workforce, scientists can also receive training in general (i.e. industry-related) or in specific (rather firm-related) topics. Furthermore, firms can encourage scientists to stay and work for them for a long time or, rather, to move on to another employer more rapidly. Scientists do therefore not only hold peculiar types of knowledge but also have particular types of skills. Interestingly, these types of qualifications seem to be inherently different capacities held by the same person. In other words, the innovative capacities of scientists seem to stem from the exchange of ideas with their colleagues on the one hand, and from an in-depth knowledge of their firm, its organization, suppliers, customers, and production processes on the other. Third, and as a corollary of the second implication, interactions of adequately skilled employees with knowledgeable scientists seem to be yet another and particularly important source of innovation. Whenever scientists learn not only from their colleagues but also from employees throughout the firm, and whenever employees at lower value-chain stages learn from scientists, these interactions seemingly facilitate a cross-fertilization of ideas which translates into the superior capacity of a firm to be radically or incrementally innovative.

As this is the case with virtually all research, the present findings and their interpretations should be taken with a grain of salt. Most importantly, these findings are based on the analyses of only one sector: pharmaceuticals. While the pharmaceutical sector is frequently studied by NIS researchers in general, and VoC scholars (most notably Steven Casper) in particular, the arguments of these literatures are proposed for the entire economy. This article, however, does not consider empirical evidence beyond the pharmaceutical sector, which implies that the present findings might not be generalizable to other industries. But given that empirical evidence lent support to the VoC and NIS arguments individually in Sections 3 and 4, there seems to be no reason to suspect that the findings on the compatibility of VoC and NIS arguments in Section 5 could not be generalized to other industries.

It can thus be concluded that the NIS and VoC literatures describe different phenomena when they illustrate how a country's research system shapes the knowledge backgrounds of scientists on the one hand, and how the economy's education and training systems provide employees with different types of skills on the other. However, these findings also suggest that the NIS and the VoC literature ignore the synergy effects resulting from the complementarities of the research and E&T systems. When pursuing RPI, IPI, and PI strategies, firms should thus be aware of the compatibility and complementarities of the NIS and VoC arguments and seek both to hire scientists with adequate knowledge backgrounds and to train their workforce in the required skills as this dramatically increases their innovative potential.

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Appendix A.

Table A.1
RPI, IPI and LCP in the UK.

Company name	Technology focus	Firm age	Competitive strategy
Acambis	Biotech	12	RPI
Amarin	Biotech	15	RPI
Antisoma	Biotech	16	RPI
CRT (Cancer Res Tech.)	Trad. Pharma	41	RPI
Celltech Group	Biotech	24	RPI
CeNeS	Biotech	7	RPI
Henderson Morley	Biotech	8	RPI
Imperial Cancer Res.	Trad. Pharma	102	RPI
KS Biomedix	Biotech	n.a.	RPI
Onyvax	Biotech	7	RPI
Pharmagene	Biotech	7	RPI
PowderJect	Biotech	11	RPI
Protherics	Biotech	5	RPI
Scotia	Biotech	20	RPI
SkyePharma	Biotech	8	RPI
Xenova	Biotech	17	RPI
AstraZeneca	Trad. Pharma	91	RPI & IPI
GlaxoSmithKline	Trad. Pharma	174	RPI & IPI
Shire	Trad. Pharma	18	RPI & IPI
Amersham Pharmacia Biotech	Trad. Pharma	n.a.	IPI
Axis Genetics	Biotech	n.a.	IPI
Bioglan	Biotech	72	IPI
Britannia	Trad. Pharma	23	IPI
British Biotech	Biotech	18	IPI
Cambridge Antibody Technology	Biotech	14	IPI
Crusade Laboratories	Biotech	5	IPI
DevCo	Trad. Pharma	5	IPI
Galen	Trad. Pharma	36	IPI
Napp	Trad. Pharma	81	IPI
Nycomed Amersham	Trad. Pharma	130	IPI
Oxford Glyco Sciences	Biotech	n.a.	IPI
Provalis	Biotech	7	IPI
Smith & Nephew	Trad. Pharma	73	IPI
Allergy Therapeutics	Trad. Pharma	70	PI
Biopharm (UK)	Biotech	n.a.	PI
Cambridge Lab.s	Trad. Pharma	17	PI
Virogen	Biotech	n.a.	PI

Source: PHID database (November 2004).

Table A.2
RPI, IPI and LCP in Germany.

Company name	Technology focus	Firm age	Competitive strategy
BASF	Trad. Pharma	139	RPI
Curacyte	Biotech	5	RPI
GPC Biotech	Biotech	7	RPI
Jerini Bio Tools	Biotech	10	RPI
MediGene	Biotech	10	RPI
Merz	Trad. Pharma	96	RPI
MorphoSys	Biotech	12	RPI
Scil Biomedicals	Biotech	5	RPI
Wilex Biotechnology	Biotech	7	RPI
ASTA Medica	Trad. Pharma	169	RPI & IPI
Bayer	Trad. Pharma	141	RPI & IPI
Boehringer Ingelheim	Trad. Pharma	119	RPI & IPI
Schering AG	Trad. Pharma	133	RPI & IPI
Altana	Trad. Pharma	27	IPI
Degussa	Trad. Pharma	5	IPI
Falk	Trad. Pharma	44	IPI
GLE Medicon	Trad. Pharma	n.a.	IPI
Gruenenthal	Trad. Pharma	58	IPI
Jenapharm	Trad. Pharma	54	IPI
Madaus	Trad. Pharma	85	IPI
Medac	Biotech	34	IPI
Merck KGaA	Trad. Pharma	336	IPI
Merckle	Trad. Pharma	59	IPI
Paion	Biotech	4	IPI
Revotar	Biotech	4	IPI
Schwarz Pharma	Trad. Pharma	58	IPI
Plantorgan	Trad. Pharma	30	PI
Schwabe	Trad. Pharma	138	PI
Strathmann	Trad. Pharma	30	PI

Source: PHID database (November 2004).

Table A.3
RPI, IPI and LCP in the Italy.

Company name	Technology focus	Firm age	Competitive strategy
Abiogen	Biotech	7	RPI
Alfa Wassermann	Trad. Pharma	56	RPI
Ausonia	Not available	n.a.	RPI
Istituto di Ricerche Sigma Tau	Trad. Pharma	19	RPI
Medioloanum	Trad. Pharma	32	RPI
Poli	Trad. Pharma	25	RPI
Rotta Research	Biotech	43	RPI
SPA	Trad. Pharma	57	RPI
Bracco	Trad. Pharma	77	RPI & IPI
Menarini	Trad. Pharma	118	RPI & IPI
Fidia	Trad. Pharma	58	IPI
Bruno	Trad. Pharma	n.a.	IPI
Chiesi	Trad. Pharma	69	IPI
Dompe	Trad. Pharma	64	IPI
Eurand	Trad. Pharma	35	IPI
Geymonat	Trad. Pharma	76	IPI
Italpharmaco	Trad. Pharma	66	IPI
Recordati	Trad. Pharma	78	IPI
Zambon	Trad. Pharma	98	IPI
Biotoscana	Biotech	n.a.	IPI
Formenti	Trad. Pharma	50	PI
Guidotti	Trad. Pharma	90	PI
Lusopharmaco	Trad. Pharma	53	PI
Mipharm	Trad. Pharma	6	PI
Neopharmed	Trad. Pharma	n.a.	PI
Rottapharm	Trad. Pharma	43	PI
Segix	Trad. Pharma	42	PI

Source: PHID database (November 2004).

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