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Currents and sub-currents in innovation flows: Explaining innovativeness using new-product announcements

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ABSTRACT

The creation of new knowledge is a haphazard process: not every sector in an economy is equally involved. The effect of industry structure on innovativeness has been a focus of attention for a long time by both academics and policymakers. In a much quoted article, using unique data – new-product announcements – Acs and Audretsch [Acs, Z.J., Audretsch, D.B., 1988. Innovation in large and small firms: an empirical analysis. American Economic Review 78(4), 678–690] identified several characteristics of industry structure and their effects on innovativeness. By analyzing a new and more consciously compiled database, we re-examine their original claims. Our results largely support their findings: industry concentration and degree of unionization for instance hamper innovation; skilled labor promotes it. Our findings diverge in one significant respect from theirs: we suggest that the large firms do *not* contribute more to an industry's innovativeness than small firms. At the industry level, we find strong support for the Schumpeter Mark I perspective of creative destruction by small firms rather than creative accumulation by large firms. In addition, we show that less dedicated innovators prove more susceptible to firm-external industry factors than more committed innovators. An unfavorable competitive environment decreases the likelihood that less successful innovators will announce new products.

1. Introduction

The creation of new knowledge is a haphazard process: not every sector in an economy is equally involved. The effect of industry structure on innovativeness has been a focus of attention for a long time by both academics and policymakers. In a much quoted article, using unique data – new-product announcements – Acs and Audretsch (1988) identified several characteristics of industry structure and their effects on innovativeness. Announcements of newly developed products are in many respects the best indicators of innovativeness. Such data are valuable and unique, but difficult to compile as well. Acs and Audretsch (1988) were among the first to use this kind of data for the US, presenting notable results. Others have followed suit (e.g. Santarelli and Piergiovanni, 1996). Analyzing similarly unique – but more reliable – data for the Netherlands, we find that innovativeness at the industry level is significantly influenced by largely the same factors found earlier. Our results diverge from Acs and Audretsch (1988) regarding the impact of average firm size on an industry's innovativeness, as well as from other findings (e.g. Aghion et al., 2005). The share of large firms within any industry impedes innovation. A Schumpeter Mark I regime – where relatively small firms dominate an industry structure – is favorable for innovativeness. This is very much in line with shared findings between our study and previous studies that indicate that for instance unionization and the presence of

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dominant players in an industry seem to hamper its innovativeness.

Our analysis is not simply an exercise in replication, however both useful and rare that is in the social sciences: we advance the analysis provided by Acs and Audretsch as well. Our data allow for analysis at the micro-level of sub-groups of individual firms, analyzing some of the sub-currents below the surface of the metaphorical innovations river. While the wealth of the data we use would also allow for many more intriguing and useful analyses, we have chosen to keep to the analytical structure developed in the early part of the paper largely in place in the second part of the paper where we focus on sub-currents, so that a coherent analysis results.

The paper proceeds as follows. Section 1 discusses the effects of industry structure on innovativeness. The method of data collection and econometric model used to explain innovativeness are elaborated in Section 2. The empirical results of our analysis at the level of industries in the economy are discussed in Section 3. Section 4 analyzes a number of sub-currents that may be discerned. Section 5 concludes both that not every sector in an economy is equally involved in innovation and that the presence of different types of firms in a sector affects its innovativeness. Young, occasionally innovating firms, that are less dedicated to innovation and (thus?) less successful innovators, respond differently to the economic structure of sectors than their counterparts.

2. Industry structure and industry innovation

In a pioneering article, Acs and Audretsch (1988) used a new and still unique indicator of innovativeness: new-product announcements. Using data on newly announced products in 1982 to determine how, at the industry level, innovativeness can be explained, they analyzed two classic themes:

(1) the relation between market structure of an industry and innovativeness, and
(2) the extent to which firm size explains innovative performance of an industry.

Using output data allowed Acs and Audretsch to shed new light on the question what determines innovativeness of different industries in the economy. Their contribution is widely recognized, as can be seen from the many citations this article has accumulated. A number of scholars have attempted to repeat the exercise, but none of them have had innovation output measures available (cf. van Dijk et al., 1997). Some studies have used the dataset that Acs and Audretsch had used for different purposes (Koeller, 1996). To the best of the authors' knowledge, the only study that gathered its own data on the innovation output of individual firms is Love and Ashcroft (1999).[2]

The argument in Acs and Audretsch (1988) is clear enough: industry characteristics that suggest decreased competitive pressure for firms, possibly through higher entry barriers, or the possibility of some stakeholders to seek rents, will hamper industry innovativeness. Thus, unionization, capital intensity, concentration and advertising are a drag for innovation. Skilled labor obviously boosts it.

The discussion of the relative merit of small versus large firms in producing innovations has attracted special attention. By providing systematic evidence on this issue, the discussion could move from a theoretical to an empirical level. At a theoretical level, no decisive arguments were found with respect to the relative benefits of either small or large firms (see Vossen, 1998, for an overview). To the extent that previous research did offer empirical evidence, the results have been "contradictory" due to the "different measures" used in these studies and a "truncated distribution of sizes where either no or only a few small firms were included" (Acs and Audretsch, 1991, p. 739).

In arguably one of the most often referred to study, Acs and Audretsch (1988, p. 679) find that "the extent to which an industry is comprised of large firms positively contributes to the total number of innovations." They also state that the innovative activity of small firms responds to different technological and economic environments than the innovation activity of large firms. In a further analysis of the same data Acs and Audretsch (1991), however, find a U-shaped relationship between firm size and 'innovative activity': both small and large firms stimulate innovation while middle-sized firms are less innovative. They did find that low-technology industries show increasing returns to firm size for innovative activity. Factors associated with a firm's market structure and technological environment determine whether or not large firms have relatively more or less advantages in being innovative (Acs and Audretsch, 1987). Large firms are likely to be more innovative when an industry is capital-intensive, concentrated, and advertising-intensive; small firms have advantages in industries that are highly innovative and where there are many large firms to start with. Nevertheless, in their 1986 article it is claimed that "the determinants of innovation are remarkably similar for large and small firms" (Acs and Audretsch, 1986, p. 110).

The discussion has not settled yet; Table 1 gives some of the studies that have been published in recent years broadly on the issue of what determines innovativeness at the industry level. Aghion et al. (2005), for instance, found an inverted-U relation between competition and innovation. Some have looked at the reverse as well: does innovativeness affect industry structure? Geroski and Pomroy (1990) argue that innovation will lead to less concentrated markets. There thus remains considerable ambiguity in the literature on the exact nature between industry structure, or competition, on the one hand, and on the other

[2] Love and Ashcroft (1999, p. 101) asked respondents within firms to "identify all new or improved products of commercial significance introduced in the 5 years preceding the study". This question is likely to introduce an upward tendency in reported cases. Imported innovations may also make up part of the reported cases, as respondents were not asked about a specific innovation and its sources. Improvements are excluded in our study. Moreover, their analysis focused on a different question than the one in this paper.

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Table 1
Competition and innovation relations—findings from selected studies

Aghion and Howitt (1992)	Innovation intensity decreases as competition intensity rises
Aghion et al. (2005)	Inverted U
Blundell et al. (1995)	Competition stimulates innovation
Boone (2000)	Increased competition will not lead to both product and process innovation
Caballero and Jaffe (1993)	Innovation intensity decreases as competition intensity rises
Cohen and Levin (1989)	Relationship of market structure and innovation fragile
Geroski (1990)	Monopoly market structure does not stimulate innovation
Kamien and Schwartz (1975)	Unclear relation between competition and innovation
Symeonidis (2001)	No evidence that price competition benefits innovation

hand innovativeness. This has been the conclusion that Reinganum (1989) drew, and it remains valid to date.

Methods and measures used in these studies are difficult to compare with each other. Thus the extent to which the findings coincide or contradict is unclear. Different measures for innovativeness are used in this literature, even though often the arguably less insightful measure of patents has been used (e.g. Aghion et al., 2005). In addition, there has been a shift in focus, primarily in the economics literature, away from the structure of an industry as a possible determinant of innovativeness towards a more direct measure for 'competition' in an industry. While the extent to which industry structure determines competitive pressure for firms in an industry varies across industries, calculating price-cost margins as a proxy for competition, as Aghion et al. (2005) and Boone (2000) do, seems riddled with methodological problems.

Both to ensure that our findings will be comparable, as well as to be able to use directly measurable variables, we follow the model and estimation approach that Acs and Audretsch (1988) have developed as closely as possible. Despite the valuable insights they have provided, their study leaves a number of questions unanswered. One obvious question is how the above findings can be reconciled with each other. In particular their findings with regard to the relative (dis-)advantages of small and large firms are inconsistent both between different studies that they have published as well as within their 1988 study if compared to the effect for the 'concentration' variable. Acs and Audretsch (1986, 1987, 1988, 1991) do not offer an explanation beyond remarks that the data have been used in different ways—either the number of innovation counts per industry or per employee within the industry is taken as the endogenous variable. The data available might not have allowed for such further analysis. In addition, since their work, the literature has progressed considerably; it is on this literature that we are able to build. The data we analyze have been compiled by ourselves—this allows us the better to understand what is at stake. The data also allow for an analysis at the level of sub-groups of individual firms, which sheds additional light on the matter. In addition, theoretical insights have progressed that allow us to interpret findings more readily than was possible in the past.

3. Data and model

The data that we use in this paper are similar to the data used by Acs and Audretsch (1988). In a number of cases, our data are more detailed and thus allow for additional analysis. We will detail this for our exogenous variables and the endogenous variable of innovativeness. The data that refer to individual companies were collected by one of the authors in 2000–2002, and as it pertains to industry as a whole, was acquired from CBS—Statistics Netherlands. The availability of data on the output of innovations at the company level is unique. Acs and Audretsch (1988) did not have access to such data, but instead used available data aggregated to the level of industries. Although their data at 4-digit industry level provides them with 247 counts compared to the 48 counts at the 2-digit level we analyzed, we are able to use our information on the level of individual firms to analyze different cross-sections of groups of firms. As such, in exploring the issue of what explains innovativeness across industries, it is now possible to identify some of the sub-currents involved.

Several measures are used in the literature to determine the innovative nature of an industry. Despite their acknowledged shortcomings, patents are often used. Yet patents as an output measure of innovation are problematic—many of them do not have any commercial value for firms (Kleinknecht et al., 2002). As a result, the propensity to patent differs widely across industries (Arundel, 2001). However, of all patents granted in the US, 55–75% lapse through failure to pay maintenance fees; if litigation against a patent's validity is a sign of commercial value of that patent, the fact that only 1.5% of patents are litigated and only 0.1% litigated to trial does not bode well (Lemley and Shapiro, 2005). Many patents thus are applied only for strategic reasons (cf. Granstrand, 2000). Obviously, patents need not be used in the further development process towards new products, services or processes. Nevertheless, patent data are readily available.

Another indicator is the extent to which current sales are due to products introduced in the last, say, 5 years. This type of data tends to be subjective and to neglect innovations that turned out to be unsuccessful. Input indicators, such as R&D expenditure or R&D personnel, have obvious drawbacks as well. The data are reasonably easily available, as they can be compiled from secondary sources such as annual reports, but the efficiency with which inputs are used varies while inputs for the R&D process need to be complemented with other inputs. The way in which such data are collected favors large and manufacturing firms for various reasons (Kleinknecht et al., 2002). In addition, such data might seem more objective than they in actual fact are—interpretation problems by the respondents and secrecy considerations obviously play a role.

We use as a measure of innovativeness the Literature-Based Innovation Output (LBIO) method, arguably the most relevant indicator of innovativeness (Kleinknecht and Bain, 1993; Kleinknecht et al., 2002; Van der Panne, 2004a). Of the different indicators generally used in innovation studies – R&D investment, dedicated research staff, or patents granted – this indicator is most in line with the crux of the Oslo Manual for collecting and interpreting technological innovation data.[3] One of the major shortcomings of this indicator may well be, however, that process innovations are not included. In the literature where advantages and disadvantages of indicators for innovativeness are discussed this has not been readily recognized. As in maturing industries the extent to which process innovations are likely to occur will be larger than for industries in an early phase of their life cycle (Klepper, 1997), there might be a slight bias against mature industries.

Thus, by screening two successive volumes of 43 specialist trade journals we are able to count the number of new-product announcements. Only announcements published on the editors' authority are counted. In the editors' expert opinion, these products embody surplus value in comparison to preceding versions or to possible substitutes. We therefore have a more objective measure of innovativeness than if we were to use advertisements. The trade journals do not have an entertainment value to the readers—the more informative they are, the more they serve the purposes of the readership. To reduce the risk of including spurious counts of innovations in our database even further, announcements must report at least one characteristic feature from which the innovation derives some superiority over preceding versions or substitutes. Newly announced products need to have improved functionality, versatility or efficiency. Consequently, the products' degree of innovativeness surpasses 'mere' product differentiation—incremental innovations or customized products for large buyers may be under-represented in this sample. Nevertheless, two-thirds of innovations reported by the trade journals in editorials were *not* invented by the company reported in the advertisement. Instead the innovations often had been instigated in the foreign mother company, or may be produced under a license. We call such innovations 'import innovations' which offer value to the users of the goods, but we do not consider them as a true sign of innovativeness. We know of no studies that could indicate the extent to which the innovations they used in their database were 'real' rather than imported innovations. As the USA is a much less open economy than the Netherlands, the share of import innovations might be smaller. On the other hand, however, for many industries the US is the most important single market. A large and increasing number of non-US firms, for instance, apply for patents in the US. These may be mistaken in the data for US innovations; we have no reason to presume that the share of import innovation is lower for the US than it is for the Netherlands. As the trade journals largely focus on readers in their capacity as entrepreneurs and managers our data might under-represent innovative new products aimed at the consumer market. The database does, however, include new products or machines that allow the purchasing firms themselves to produce new goods for consumer markets.

As we are concerned with innovative firms only, we excluded imported innovations from the sample by contacting every single new-product announcing firm. Out of 1056 responding firms, 658 or 62.3% reported that the announced innovation was imported rather than developed in-house within the Netherlands.[4] Further analysis (not presented here) shows that this share of foreign products varies across industries randomly and ranges from 0 to 100%. In the absence of origin verification, the LBIO data cannot be considered fully unbiased across industries. Having omitted these spurious counts, our database documents 398 valid counts of new-product announcing firms, covering 48 industries.[5] These 48 industries cover almost the entire Dutch economy—primarily agriculture and logistics are not included. As such, we can confidently say that our database comes as close to covering the complete population of new-product announcing firms as possible.

Thus, we have data on an industry's R&D expenditures (INDUSTRYR&D). The average capital intensity is measured as capital assets relative to industry output (CAPITALINTENSITY). Acs and Audretsch's term 'value of shipment' we take to be synonymous with company output or sales. Fixed assets may or may not be combined with current assets. There turns out to be no difference in the analysis if one takes fixed assets only, or in combination with current assets, which is a remarkable finding. Acs and Audretsch used the C4 ratio – a ratio for the market share of the four biggest firms in an industry – as a measure of concentration in the industry. We used a similar measure – the number of firms divided by the number of employees in the industries, relative to the national average (CONCENTRATION) – thus having a measure that covers the entire industry, and not just the large firms within it. Others have found this measure to be more useful as well (Feldman and Audretsch, 1999). Unionization is measured in the same way as Acs and Audretsch do: percentage of employees who are a member of a union (UNIONIZATION). Marketing expenditures divided by company output provide a proxy for advertising intensity (ADVERTISING). The large-firm employment share, to Acs and Audretsch, is indicated by the share in total industry employment accounted for by companies larger than 500 employees (LARGEFIRMSHARE). This cut-off point was chosen for convenience: this is how data are made available.[6] We had to use different cut-off points—indeed we were able to choose from among the following points: 74.5, 149.5, 349.5, and 624.5. We analyzed different versions of our model using these different cut-off points and found no significant difference in the nature of the results. Why, at least in this range, the employment share of large firms seems to affect the innovativeness at the industry level in consistently the same way will be discussed at more length in the subsequent section. Given that tiny or small firms

[3] The first edition of the Oslo Manual stipulated that an innovating firm "is one that has implemented technologically new or significantly improved products or processes or combinations of products and processes" (OECD, 1992, p. 42). See Santarelli and Piergiovanni (1996) for an extensive and illuminating discussion of merits and shortcomings of such a literature-based innovation output indicator as well.

[4] 1585 announcing firms were surveyed; 66.6% responded.

[5] Data used by Acs and Audretsch (1988) cover 247 industries at the 4-digit SIC industry code level.

[6] Personal communication, D. Audretsch.

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typically represent the majority of firms in an economy, it is of importance not to neglect such firms. Effects due to differences in industry size are controlled for by including a variable for total sales (INDUSTRYSIZE). The percentage of employees who have obtained a degree at bachelor or master level indicates the level of skill available (SKILLEDLABOR). This is a much more clearly defined measure than the one used by Acs and Audretsch ("the percentage of employment consisting of professional and kindred workers, plus managers and administrators, plus craftsmen and kindred workers"). Our definition might undervalue experience relative to formal training. We have added a further control variable for the size of the population of firms in an industry (FIRMPOPULATION); it is an integer for the number of firms in an industry. A larger population of firms in an industry might contribute to innovativeness of that industry by, for instance, increasing knowledge spill-over (cf. Marshall, 1890; Van der Panne, 2004b; Audretsch and Keilbach, 2008). The variable FIRMPOPULATION is statistically as well as theoretically unrelated to the other variables used and so its inclusion does not cause any model specification problems.

It is clear that the data thus gathered allow for a large number of different types of analyses. Indeed, the data have been employed that way by the authors (Van der Panne, 2004a,b). What is equally clear is that by aggregating the data to industry level, some of the information that could be of use to answer other research questions is lost. In this paper, however, we are interested particularly in the effects of industry characteristics on industry innovativeness. We do use the micro-data available to look at cross-sections of firms. We thus analyze the extent to which innovativeness of an industry is affected by the fact that a particular sub-set of firms is present. We specifically look at four sub-currents in our data, contrasting: young and older firms, occasionally and permanently innovating firms, firms with high or low R&D intensity, as well as most and least successful innovators. In particular the reason for focusing on younger versus older firms may need some explanation. Ten years is a threshold, as during that period, a knowledge base or absorptive capacity of some kind can be assumed to have been established. The first 10-year period exhibits the most dramatic variation in firms' growth paths (Garnsey, 1998; Stam and Garnsey, 2006).

While both the replication of the analysis of Acs and Audretsch (1988) and the extensions in this paper offer substantial contributions to the understanding in the literature of innovation processes, we acknowledge that much more analyses are possible using this set of data.

Some descriptive statistics might give an impression of the kind of data we use (see Table 2). We compare our LBIO data with data regarding innovation collected by the Dutch Statistical office as part of the Community Innovation Survey (CIS). This comparison is of particular interest for two related reasons. Firstly, CIS mainly uses R&D input as a measure of innovativeness. Secondly, CIS does not cover firms employing fewer than 10 employees. Obviously, in smaller firms the innovation process is likely to be more ad hoc. Activities aimed at developing new knowledge or products are not so likely to be recognized. The distribution of innovations included in our database is not biased according to economic activity in terms of industries. The 48 industries at 2-digit level covered in this study include 10 service industries, also at the 2-digit level. Acs and Audretsch analyzed their data at the 4-digit level, but limited their research to the manufacturing industries. While the service industries, on average, contribute less to the knowledge economy than the average firm (Leydesdorff et al., 2006), their contribution should not to be neglected. Small and medium-sized enterprises (SMEs) tend to be under-represented in innovation studies as surveys constructed to measure innovative activity tend to neglect small firms. In contrast to a number of other studies that use a different indicator for innovation, our data covers all the firms that announced a new product. Unlike CIS and other survey-based data on innovativeness, we have not drawn a sample from a larger population to send our survey to. We can thus be fairly certain that we have a complete view of innovation in the Netherlands.

Table 2
Some descriptive statistics

			CIS	LBIO
R&D intensity				
		Mean	7	8.9
		Median	2.2	5
		S.D.	66.7	12.9
R&D output				
	Improved	Mean	20.8	23.3
		Median	15	20
		S.D.	20.7	16.1
	New	Mean	11.3	24.1
		Median	8	20
		S.D.	14.6	20.51
Patents				
	Yes		28.3%	51.3%
R&D activities				
	Permanent		72.0%	82.2%

In Table 2, it can be observed that the firms identified by the LBIO method engage more often in R&D on a sustained (rather than occasional) basis than do CIS firms. The total sales generated by the new or renewed products are higher as well. LBIO firms tend to patent more often. In general, the descriptive statistics show that the LBIO method of collecting data on innovativeness presents averages for R&D intensity, innovation commitment, patenting behavior, and R&D output, in terms of improved as well as new products, that are higher than indicated by the CIS data. Is some of the lamenting about Dutch and European firms not being innovative enough unwarranted (Baumol, 2004)? Possibly so—firms identified by the LBIO method do not (have to) rely on secrecy to appropriate the benefits of their innovative efforts and tend to patent more. This aspect of the methodology might have affected the data.

Using the data as described above, we estimate the following model using a negative binomial regression model:

$$\begin{aligned}\mathrm{LBIO}_i &= \alpha + \beta_1(\mathrm{CAPITALINTENSITY}_i)\\ &\quad + \beta_2(\mathrm{CONCENTRATION}_i) + \beta_3(\mathrm{UNIONIZATION}_i)\\ &\quad + \beta_4(\mathrm{ADVERTISING}_i) + \beta_5(\mathrm{SKILLEDLABOR}_i)\end{aligned}$$

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$$+\beta_6(\text{LARGEFIRMSHARE-X}_i) + \beta_7(\text{INDUSTRYR\&D}_i) +\beta_8(\text{INDUSTRYSIZE}_i) + \beta_9(\text{FIRMPOPULATION}_i)+\varepsilon_i \quad (1)$$

where i = 1.48 industries.

We are unable to perform an ordinary regression analysis, in the way Acs and Audretsch did, as it cannot be assumed that variables are normally distributed. We do, however, and contrary to Acs and Audretsch, standardize coefficients so as to make the comparison of our results in Table 3 between variables possible. The count of innovating firms follows a Poisson distribution, suggesting the use of a count data model. However, for reasons of over-dispersion, the negative binomial regression model is more appropriate (Cameron and Trivedi, 1986).[7] Statistically, this method yields results that are comparable to a regression analysis, and it thus is a widely used method in the social sciences. When statistically significant findings do emerge from the analysis, they are scientifically meaningful as well.[8]

4. Innovativeness at industry level

The results of our regression analysis at industry level are presented in Table 3. These are largely in line with what Acs and Audretsch (1988) found in their study. What explains innovativeness at the industry level would appear not to vary too much over time and across countries. This constitutes an important contribution to the ongoing debate about the question of what explains innovative patterns. Like Acs and Audretsch, we find that additional R&D effort by firms in an industry generally contributes positively to the number of innovations produced (see also Acs et al., 1994). In line with their implicit rent-seeking argument, we found that concentration and unionization in an industry affect innovativeness negatively. The coefficient for unionization is statistically insignificant, however, which may be related to either the low degree of unionization of employees in the Netherlands or (possibly) the compliant behavior of unions.

Advertising affects innovativeness negatively. This might be because incumbents focus on existing markets for which no new products are deemed necessary (cf. Christensen, 1997). Advertising intensity might be an entry barrier for new firms in particular (Geroski, 1995). Moreover money used for advertising cannot be spent on innovative efforts. It could also be linked to our method of collecting data in that we took data from editorials in which innovations were announced. Editors of these trade journals might decide not to discuss new products that might be or have been advertised. Capital intensity negatively affects innovativeness for the probably the same reasons and in the same way as advertising does: newly developed products might make existing investment in (sunk) production capacity obsolete. Firms may decide not to develop new products that cannibalize existing markets for which they have made substantial investment in terms of production capacity. Capital intensity was also found to be an entry barrier (Geroski, 1995). As is to be expected, the presence of skilled labor in an industry positively affects innovativeness. This may differ according to educational level or acquired skills, but we did not include this in our analysis (however, compare Van der Panne and Dolfsma, 2003).

Our most significant finding, where we differ from Acs and Audretsch, is the effect of employment share on innovativeness at industry level (see Table 3). Large-firm employment share may of course be different from the degree of concentration in an industry. Acs and Audretsch (1988) found that firms larger than 500 employees are significantly more innovative than smaller firms. This finding – support for the Schumpeter Mark II point of view – has drawn a lot of attention in the literature (e.g. Cohen and Klepper, 1996). However, we consistently find that large-firm dominance of an industry has a negative effect on innovativeness in that industry. Analyzing several versions of the model – where we altered the threshold for defining large firms; 74.5, 149.5, 349.5, or 624.5 employees[9] – does not change the results: coefficients are negative in all these cases. As the cut-off points increase, the betas become more negative. Except for the cut-off for large-firm employment share at just 74.5 employees, all these findings are statistically significant at the 1% level. This is clearly in line with what the early Schumpeter argued, and thus provides support for the so-called Schumpeter Mark I proposition. Industries with a substantial presence of small companies are more likely to be innovative than industries where large companies dominate.

The above results establish statistical associations between an array of industry characteristics and new products announced by innovative firms. Yet these associations need not be equal for various sub-groups of firms. Our understanding of the relations established in Table 2 above may thus be improved by analyzing a similar model for different sub-sets of firms. The data we have on the level of the individual firms allow us to categorize them in order to establish whether indicators for the competitive environment have a similar effect on innovativeness for different sub-sets. Our data permit closer explorations of the sub-currents of innovations at the micro-level of individual firms, since we compiled data on every single new-product announcement reflecting a firm's innovation efforts. In our subsequent analysis we compare models for (I) continuously innovating and occasionally innovating firms, (II) young with old firms, (III) the least with the most R&D-intensive firms, and (IV) successful with unsuccessful innovators and analyze the extent to which industry characteristics affect innovativeness. The results for these

[7] In the case of over-dispersion, i.e. $\sigma_i > \mu_i$, the Poisson model underestimates dispersion, resulting in downward biased standard errors (Cameron and Trivedi, 1986). The negative binomial regression model addresses this issue by introducing the parameter α, reflecting unobserved heterogeneity among observations. A consequence of the downward biased standard errors is that this estimation model is more conservative than a standard Poisson model for count data.

[8] The measure for statistical fit of the model with the observed data, R^2, ranging between roughly 20 and 40%, is quite common in social science research.

[9] The results of models with cut-off points for large firm employment shares that are not presented in Table 3 (for 74.5, 149.5, and 624.5 employees) may be obtained from the authors.

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Table 3
Regression of total number of innovators, 2-digit SIC industry level

	Percentage change in expected count[a]	Model estimated by Acs and Audretsch (1988)
Industry characteristics		
Capital intensity	−79.5 (0.007)***	Negative sign, *not* significant
Concentration	−91.7 (0.001)***	Negative sign, significant (5%)
Unionization	−20.0 (0.537)	Negative sign, significant (5%)
Advertising	−72.4 (0.040)**	Negative sign, *not* significant
Skilled labor	216.2 (0.001)***	Positive sign, significant (5%)
Large-firm share[b]	−71.9 (0.001)***	Positive sign, significant (5%)
Control variables		
Industry R&D	198.5 (0.002)***	Positive sign, significant (5%)
Industry size	272.0 (0.009)***	Positive sign, significant (5%)
Firm population Constant	22.1 (0.487)	–
N	48	247
R^2	0.19	0.48

*Significant at 10%; **significant at 5% level; ***significant at 1% level; p-values in parentheses.
[a] Percentage change in expected counts per standard deviation increase in explanatory variables.
[b] Minimum size threshold large firms: 350 employees.

sub-currents are presented as four different statistical models in Table 4.

5. Innovation sub-currents

Geroski et al. (1993, p. 207) have stated that identifying, let alone measuring, the 'inherent differences' between groups of innovating firms is a difficult undertaking. We submit that the sub-currents analyzed here go some way towards that end. Before we start discussing what can be established based on the findings shown in Table 4, we need to make clear what cannot be established. Because of the nature of our data, and specifically due to the size of our database, we cannot in all cases establish statistically whether the coefficients presented for each sub-set within a model are significantly different from those of the other sub-set in that same model. Such a comparison is not possible between the models of Table 4, or between any of the models and Table 3. However, in addition to statistical significance one should also consider theoretical significance (e.g. McCloskey and Ziliak, 1996): particular betas in an empirical analysis, while possibly not statistically significant, can constitute theoretically important findings. What is more, however, *within* each model patterns can be established by determining which coefficients for which variable do and which do not differ significantly in a statistical sense from zero. Such comparison is possible with Table 3 as well.

Some of the betas are remarkably similar both across the four models presented in Table 4 as well as between Tables 3 and 4. In this study, the effects of capital intensity, concentration ratio in an industry and large-firm (employment) are comparable in every specification of our model. Acs and Audretsch found similar effects for these variables. This could be taken as evidence that these are the types of indicators that could be affected by a general policy. If government policy aimed at stimulating particular sub-groups of firms, it might not be appropriate to seek to influence the betas for these variables. Given the similarity of the findings reported here with those of Acs and Audretsch, these variables would seem to be appropriate indicators for National Innovation Systems (cf. Balzat and Hanusch, 2004; Leydesdorff et al., 2006; Lundvall, 1992; Nelson, 1993). If the data and methodology used are sufficiently comparable, the betas themselves might then be ways of comparing different national systems.

The variables skilled labor and advertising can help focus government policy that aims to stimulate particular sub-groups of firms, in that their effects are seen to differ between the sub-currents as shown in Table 4. We will elaborate on this and other issues in our discussion of the sub-currents. The effects of unionization on innovativeness do not differ much in our study. The effect of unionization is negative, as Acs and Audretsch found, yet its effect is insignificant. We have no reason to suggest that unionization is either a general feature of national innovation systems, or a way to distinguish and compare systems.

To recapitulate, the first three models of Table 4 discriminate between firms in the sample using R&D input measures, while Model IV analyzes a sub-set of firms selected according to an innovative output measure.

5.1. Sub-current I: nature of R&D effort

Comparison of the permanently innovating firms with occasionally innovating firms (Model I) shows that the latter appear more responsive to industry characteristics. For every standard deviation increase in capital intensity, the expected count of occasionally innovating firms in that industry decreases some 92%, compared to only 77% for permanently innovating firms. A different responsiveness also holds for changes in the industries' concentration ratio, large-firm dominance, but particularly for the proportion of skilled laborers. The occasionally innovating firms seem to do well in industries that are growing in both size and number of players, but less so in industries with high R&D efforts. Permanently innovating firms are not really affected by the number of firms in an industry. Occasionally innovating firms are also the most likely to benefit from the employment of additional numbers of skilled laborers. Their base of skilled labor may, of course, have been low to start with. Occasionally innovating firms are more likely to be hurt by an emphasis on advertising in an industry than

Table 4
Sub-currents of innovations[a]

	Model I, nature of R&D efforts		Model II, firm age		Model III, innovation intensity		Model IV, innovation performance	
	Permanently innovating firms	Occasionally innovating firms	Old firms	Young firms[b]	33% most R&D-intensive firms[c]	33% least R&D-intensive firms[d]	33% most successful innovators[e]	33%least successful innovators[f]
Industry characteristics								
Capital intensity	−77.3*** (0.01)	−91.9*** (0.01)	−77.7*** (0.01)	−78.0*** (0.01)	−83.7*** (0.01)	−56.4* (0.08)	−71.1*** (0.01)	−75.0*** (0.01)
Concentration	−90.9*** (0.01)	−97.8*** (0.01)	−91.4*** (0.01)	−94.7*** (0.01)	−85.9*** (0.01)	−95.1** (0.02)	−84.1*** (0.01)	−98.8*** (0.01)
Unionization	−14.6 (0.65)	−3.8 (0.92)	−34.0 (0.32)	−27.1 (0.30)	42.4 (0.38)	−45.0 (0.11)	−27.2 (0.43)	−48.0** (0.05)
Advertising	−67.5* (0.08)	−67.3*** (0.01)	−75.5** (0.02)	−35.4 (0.19)	−55.0 (0.11)	−66.3** (0.05)	−62.4** (0.04)	−42.3 (0.11)
Skilled labor	218.5*** (0.01)	343.7*** (0.01)	157.1* (0.10)	287.0*** (0.01)	333.4*** (0.01)	79.4** (0.04)	167.9*** (0.01)	232.6*** (0.01)
Large-firm share[a]	−70.8*** (0.01)	−91.7*** (0.01)	−71.6*** (0.01)	−85.2*** (0.01)	−69.3*** (0.01)	−69.4*** (0.01)	−60.2*** (0.01)	−90.6*** (0.01)
Control variables								
Industry R&D	190.8*** (0.01)	151.6*** (0.01)	212.0*** (0.01)	90.6*** (0.01)	160.9** (0.02)	124.2** (0.02)	156.4*** (0.01)	100.6*** (0.01)
Industry size	231.9** (0.02)	301.4*** (0.01)	283.8*** (0.01)	127.5*** (0.01)	199.8*** (0.01)	183.1** (0.02)	152.5** (0.02)	141.1*** (0.01)
Firm population	15.0 (0.61)	58.6* (0.06)	20.2 (0.58)	32.4* (0.06)	20.7 (0.47)	77.1 (0.20)	20.4 (0.41)	73.9*** (0.01)
Constant	(0.05)**	(0.01)***					(0.22)	(0.01)***
Number of observations	48	48	48	48	48	48	48	48
R^2	0.19	0.34	0.20	0.41	0.24	0.23	0.21	0.30

IQR = Inter Quartile Range. *Significant at 10% level; ** significant at 5% level; *** significant at 1% level; *p*-values in parentheses.

[a] Percentage change in expected counts per standard deviation increase in explanatory variables, robust standard errors.

[b] Firms younger than 10 years: 145 firms.

[c] R&D expenses exceeding 15% of total sales, IQR = 20–52%.

[d] R&D expenses less than 5 percent of total sales, IQR = 1–4%.

[e] Share of total sales generated with new/renewed products less than 30%, IQR = 0–20%.

[f] Share of total sales generated with new/renewed products exceeding 60%, IQR = 70–85%.

permanently innovating firms—the effect on the latter is hardly significant.

5.2. Sub-current II: firm age

As regards the firms' age (Model II), young firms are more responsive for the variables industry concentration, capital intensity and large firms' employment share. Young firms will be much less inclined to innovate as industry R&D or industry size increase. Their response to increases in the number of firms in an industry is concomitantly more pronounced than that of old firms (not significant in the latter case). Young innovating firms flourish in industries with expanding firm population. With respect to the share of skilled laborers, young innovating firms seem more responsive than established innovating firms. The effect of employing additional skilled labor is hardly significant in old firms—for these firms there seem to be decreasing marginal returns to hiring skilled labor. Young firms especially benefit from the availability of additional skilled labor in their industry. Young firms are hardly affected by being in an industry that is fraught with a need for advertising. Old firms are significantly affected: the beta here is the most pronounced in any of our analyses. One may possibly argue that newly established firms focus on the introduction of new products, whereas incumbent innovators focus on process innovations, possibly to extend a product life cycle.[10] Scale effects, in terms of industry turnover and industry R&D, stimulate older firms more than the younger ones to be innovative.

5.3. Sub-current III: innovation intensity

Concentration, advertising and unionization (well-nigh significant) negatively affect the least more severely than the most R&D-intensive firms in their propensity to announce new products (Model III). Capital intensity is more of an impediment for R&D-intensive firms. The effect of advertising is insignificant for the high R&D-intensive firms. Even though not statistically significant, it is striking to observe that unionization positively affects the extent to which the most R&D-intensive firms are likely to innovate. As the contribution of skilled labor is particularly high for this group as well, it appears that a committed, skilled workforce might be beneficial in this case. The effect of additional skilled labor is exceptionally low (though positive) for the least R&D-intensive firms; the effect of unionization on the least R&D-intensive shows the second most negative beta and is on the verge of being statistically significant.

5.4. Sub-current IV: innovation performance

These findings translate into innovative performance in terms of sales generated by new or renewed products (Model IV).[11] The competitive environment, as defined by industry characteristics, impedes the innovativeness of less successful innovators in particular. Indeed, this is the only group where unionization has a statistically significant effect (negative) on innovation. The effect of concentration is also most pronounced (again, negatively) for this sub-group of least successful innovators. As the large-firm employment share shows one of the most pronounced (negative) effects as well, it would appear that this group is in a difficult position. Increasing industry R&D, which generates external knowledge economies, particularly benefits the most successful innovators. The least successful innovators are, however, more responsive to large-firm employment share. Surprisingly, the least successful innovators are more likely to innovate as industry population increases; with a large beta, this is the only instance for the population size variable to be significant at the 1% level. The least successful firms are stimulated more by entry than by the innovativeness of (large) incumbents—cf. large-firm employment share. This finding is consistent with what Geroski (1995) argued. For the least successful firms, adding skilled labor will improve their innovation track record. The negative impact of advertising is also far less pronounced for the less successful innovators. Possibly the relatively small portfolio of newly developed products induces the less successful innovator to rely on advertising in an attempt to extend the life cycle of their established products. Below we show that the least successful innovators tend to be the older firms. The contribution that additional skilled labor makes to the most successful firms is surprisingly low—they may already have highly skilled laborers in sufficient numbers.

5.5. Joint sub-currents

A chi-square test indicates that firm age (Model II) and nature of R&D-effort – permanent or occasional (Model I) – are not related: there is no overlap between these groups. Of all firms in the database younger than 10 years 79.6% are permanent innovators, of all those older 78.7% are. R&D-intensity (Model III) and the nature of the R&D-effort (Model I) also are not statistically related: the *p*-value of a chi-square test is not significant. Additional R&D expenditure need not translate into more continual innovation efforts—firms can be engaged in large but short-term R&D projects. Determining whether Models II and III overlap, we found that younger firms do tend to be more R&D-intensive than older firms. Some of these firms may have been set up as spin-offs or otherwise to bring a new product to market. In the survey, 37% of the group of firms established up to 5 years prior to the survey indicated that the innovations announced in trade journals were the reason for the firm to be established.

The firms most successful at innovation are also likely to be most involved in R&D (Models IV and III compared).

[10] One would then, however, have expected substantially higher betas for capital intensity and concentration for old firms as compared to young firms, which is not the case. The effects of concentration and capital intensity are, however, highly sector-specific, depending for example on a sector's maturity.

[11] Measuring performance in terms of profitability, Geroski et al. (1993, p. 209) find that "innovating firms enjoy higher margins . . . have larger market shares . . . [while their profit margins] . . . are somewhat less sensitive to cyclical downturns than those of non-innovators."

R&D effort does seem to translate into success: 53% of the high R&D-intensive firms are among the most successful. In a chi-square test this is statistically significant. It should therefore not be surprising to see that successful innovators are likely to be innovating on a permanent basis (Models I and IV compared)—some 92% are. Conversely, of all firms permanently involved in innovation, only 28% are among the most successful. Successful firms also tend to be established less than 10 years prior to when survey was conducted (Models II and IV compared). Of the young firms, 35.6% are among the most successful; and among the successful firms, 47% are younger than 10 years of age. There is thus some overlap between the different sub-groups analyzed in the four different models shown in Table 3—the overlap is, however, modest.

5.6. *Some additional findings not presented in Table 4*

In addition to the analysis of sub-sets of Dutch innovative firms presented in Table 4, we also categorized the dataset in two other ways. In line with what would be expected, as they are by definition more involved with third parties (Dolfsma, 2004), service firms are more responsive, in terms of innovativeness, to their competitive environment. The finding that innovative firms that have been granted a patent are more responsive to their competitive environment confirms the idea that patenting might indeed be motivated by strategic considerations (cf. Dolfsma, 2006).

An important concluding generalization to this section, which analyzes sub-currents in the metaphorical innovation river, is that less dedicated innovators – those firms that only occasionally innovate, are R&D-extensive firms, and are (thus) the least successful – tend to be (somewhat) more sensitive to the competitive environment they find themselves in.[12]

6. Concluding remarks

Following Acs and Audretsch (1988) in their seminal work, this study uses announcements of innovative products in editorials of trade journals as its indicator of innovativeness. We find that the innovativeness of Dutch firms at industry level is determined largely by the same factors as Acs and Audretsch found. Innovativeness at industry level may thus be a fairly stable factor across time and between countries. In particular, measures that point to the extent to which agents can appropriate rents in an industry, such as industry concentration and unionization, hampers innovation. Skilled laborers employed and additional expenditure on R&D promotes innovation. Sectors in the economy are thus involved in innovation, the production of new products and services based on new knowledge, to varying degrees.

Our results largely support the findings of Acs and Audretsch, but diverge from them in one important way. We suggest that the large firms do *not* contribute more to an industry's innovativeness than small firms. By using a number of different cut-off points, we find that innovativeness is *negatively* related to large-firm employment share. This amounts to a clear vindication of the Schumpeter Mark I hypothesis: small firms will announce significantly more new products than large firms.

Using data at the firm level, we are able to analyze notable sub-currents below the surface of this innovation river. We contrasted occasionally with permanently innovating firms, old with young firms, R&D-intensive with R&D-extensive firms, and most successful with least successful innovators. In general, we found that less dedicated innovators prove more susceptible to environmental factors than more dedicated innovators (cf. Geroski et al., 1993). In addition, an unfavorable competitive environment decreases the likelihood for the least successful innovators to announce new products. Presence of different types of firms in a sector affects its innovativeness. Young, occasionally innovating firms, that are less dedicated to innovation and (thus?) less successful innovators, respond differently to the economic structure of sectors than their counterparts.

Obviously there is a need to substantiate the findings for innovation sub-currents we report in this study, both for the Dutch innovation system as well as for other innovation systems. We believe that there is an urgent need to study further the sub-currents that surge just below the surface of the metaphorical innovation river. This innovation river is, to take this metaphor just a small step further, not a smooth, calmly flowing, homogeneous river but rather one where the sub-currents may take slightly and, sometimes, dramatically different courses. We have been able to offer insights into only some of these sub-currents.

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[12] Generally, R^2-s are higher, betas are more significant, and betas are larger in absolute terms for the models that estimate innovative behavior of firms that are less dedicated to innovation.

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